Emerging stock market microstructure: empirical studies of the National Stock Exchange of India

EMERGING STOCK MARKET MICROSTRUCTURE: EMPIRICAL STUDIES OF THE NATIONAL STOCK EXCHANGE OF INDIA

by

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ABSTRACT

This thesis adopts an empirical approach to examine various market microstructure issues, using data from the National Stock Exchange of India (NSE). Whilst the respective empirical analyses may be considered as self-contained investigations, they are primarily linked through the common objective of understanding the mechanics of the pricing process as it occurs on actual markets, using the NSE as exemplar.

The first major focus of the dissertation is non-synchronous trading: empirical evidence of non-synchronicity is obtained by testing for predictability as between indices of different levels of liquidity. A simple test of the analysis of trading-break returns is proposed to infer whether predictability may be mainly attributable to non-synchronous trading or whether it constitutes a delayed adjustment of traders' expectations.

The second question tackled in the thesis is whether volatility on the NSE may be considered as justified or excessive. Rather than adopting the established methodology of comparing stock price changes to information about expected dividends, the research question is split up into two subsidiary ones. The first question is whether volatility is related to information flows, whilst the second related question concerns the relationship between volatility and returns. Three sources of excessive volatility are pin-pointed. Monday effects are found in index data but not in the underlying stocks – indicating index fluctuations which are not information-related. A second indicator of excessive price movements is the pronounced volatility which coincides with the fiscal year end of quoted companies but which is not accompanied by a similar increase in long-term returns. A third indication of unjustified price fluctuations is that volatility seems unrelated to returns when considering a long-term time series.

The third topic of the thesis relates to the efficacy of opening and closing call auctions. This issue may be considered as the crux of the dissertation and it is tackled by analysing the effects of the suspension of a call auction system on NSE. Changes in volatility, efficiency and liquidity following the suspension are analysed, and an event study is presented. The relationship between call auctions and long-term volatility is also investigated. The findings suggest that the expected benefits of call auctions may not always materialise, possibly due to an inappropriately structured auction, or because a liquidity threshold for stocks must be surpassed for the expected benefits to accrue.

Keywords:
Call Auctions, Excessive Volatility, Monday Effects, National Stock Exchange of India, Non-Synchronous Trading, Stock Market Microstructure, Volatility Seasonality

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BRIEF CONTENTS

TABLE OF CONTENTS

EMERGING STOCK MARKET MICROSTRUCTURE: EMPIRICAL STUDIES OF THE NATIONAL STOCK EXCHANGE OF INDIA

CHAPTER 1:
INTRODUCTION

Asset pricing is a central issue in finance. Traditionally, stock prices were considered to be determined by a simple intersection point between demand and supply curves; yet this approach abstracts from numerous features of real markets, including information asymmetries, differing expectations of market participants, the trading setup, and fluctuations in liquidity. The study of market microstructure endeavours to understand the pricing process taking place on real markets whilst accounting for the special features of individual markets, particularly the trading setup.

Market microstructure studies are relevant to emerging markets. Considering that the discipline is relatively new, the majority of publications tended to focus on established markets such as US and UK ones. Yet, the discipline may be further enriched through studies using emerging markets data since one may expect differences between the microstructure effects of stock market trading in emerging economies and those in the industrial economies. As compared with developed stock markets, emerging markets tend to exhibit: higher serial correlation, less frequent trading, slower adjustment of prices to news, and indirect evidence of more insider trading as discussed by Bekaert and Harvey (2002). Extending market microstructure research to focus on emerging markets also constitutes an important objective when considering the increased interest in such markets on part of finance practitioners.

This dissertation takes an empirical approach in analysing distinct market microstructure issues relating to price formation. Empirical studies offer particular advantages. For instance, the behaviour of market participants may be modelled without resorting to unobservable factors such as indifference curves, the degree of risk aversion, and inventory holdings.

Whilst the empirical investigations in this dissertation tackle different market microstructure aspects, they are linked through the quest to understand and to model the pricing process as it occurs on actual markets. In particular, the dissertation tackles three major issues as outlined below.

The first issue relates to the way in which stock prices may be subject to non-synchronous trading effects, emanating from temporary trading pauses of particular securities. Such pauses imply that the last trading price will typically become outdated as new information becomes available. The detection of non-synchronous trading effects is important on several grounds. Non-synchronicity may be mistakenly interpreted as a delayed adjustment of traders' expectations or as an opportunity for realising abnormal profits given that the latest trading price does not fully reflect all available information. In addition, the detection of non-synchronous trading effects constitutes an important step in understanding particular characteristics of high-frequency data and in designing market setups which minimise trading pauses and thus curtail non-synchronous trading. The first empirical investigation of this dissertation, presents evidence of the outcomes of non-synchronicity in terms of lead-lag effects. A new methodology is proposed in order to infer whether predictability may be attributed mainly to non-synchronicity or to delayed adjustments of traders' expectations. It is noted that non-synchronous trading effects may become more evident in high-frequency data – and this may be attributed to the fact that the surge in trading activity at the end of the day may dampen the degree of non-synchronicity as inferred through daily closing prices.

The second major aspect of the dissertation is the deviation of prices around their "true" values – particularly the seasonal pattern of volatility. The importance of this issue lies not only in the fact that volatility is directly related to risks and to returns, but also in view of market designers' efforts at curtailing excessive volatility. The starting point of the second empirical investigation consists of the well-established seasonality patterns documented in prior literature – such patterns were used to pin-point sources of excessive volatility in stock prices. This investigation is particularly important in that it evaluates determinants of asset price fluctuations in the absence of data about dividend expectations, which constitutes the established method of detecting unjustified price fluctuations.

The third major issue is whether call auctions may enhance the pricing process in terms of inducing higher efficiency and liquidity and curtailing volatility. This topic relates to one of the main branches of market microstructure since it involves the design of trading protocols and the evaluation of their efficacy. One noteworthy feature of the two empirical investigations relating to call auction efficacy is the focus on the suspension of a call auction system. This approach is not only significant given that it was not adopted in prior research, but also since other features of the trading protocol remained unchanged. Thus changes following call auction suspension are more likely to be the result of the suspension itself rather than accompanying modifications of the trading protocol. The third and the fourth empirical investigations evaluate whether the suspension of a call auction system resulted in improvements (or deterioration) in volatility, efficiency and liquidity. Whilst the overall results are not clear-cut, only little evidence was obtained to suggest that call auctions are necessarily beneficial, and possible reasons for this are proposed.

The empirical investigations in this dissertation have a common ultimate goal: to gain further understanding of the pricing process on securities markets. This goal is pursued from three different viewpoints. The dissertation presents a number of findings which broaden the body of academic knowledge, and are also relevant for market designers to formulate policies to improve the pricing process and to enhance market efficiency.

The empirical investigations in this dissertation can be viewed as four self-contained studies. However, there also are important links among these studies. For instance, non-synchronous trading effects are relevant to explain particular volatility features, such as a Monday effect in index data which is not evident in individual stock data. Similarly, the results on volatility seasonality help to interpret the empirical results on volatility changes following the call auction suspension. Thus, the first two empirical chapters also serve as a detailed background to the subsequent studies of the call auction suspension.

The setting which was selected for conducting the empirical studies was the National Stock Exchange of India (NSE). This choice is attributable to different reasons. Firstly, it offers the opportunity to investigate the microstructure of an emerging market when most of the existing research is concerned with mature markets. An additional noteworthy feature was the availability of detailed data obtained from NSE. Furthermore, the increased interest in Indian markets on part of finance practitioners implies a higher potential for conducting studies which are of interest both from a scholarly and from a practical point of view. India provides an interesting empirical setting in view of the considerable improvements which were undertaken in the Indian capital market during the 1990s. These include the establishment of a regulator (Securities and Exchange Board of India), the setting up of NSE which proved a significant competitor of the Bombay (Mumbai) Stock Exchange (BSE), and the dematerialization of securities.

This dissertation is structured as follows. Chapter 2 shows a review of the basic literature, consisting of core market microstructure papers. Further literature searches were also required in the context of the empirical studies, namely: non-synchronous trading effects, volatility, and the efficacy of call auctions. This body of focused literature is presented as an individual section within each empirical study. The fourth empirical investigation should be read in the context of the third one, and therefore it does not have a designated literature section.

Chapter 3 describes the empirical setting and outlines the main features of the data set. The subsequent four chapters show the empirical investigations. Chapter 4 analyses the impacts of non-synchronous trading on predictability, whilst Chapter 5 inquires whether NSE stock prices are excessively volatile. Chapter 6 investigates the general market impacts of the suspension of an opening and closing call auction system and this may be considered as the most important chapter of the dissertation. The subsequent chapter elaborates on the same issue by considering changes in volatility following the suspension. Chapter 8 concludes.

The main contributions of this thesis may be summarised as follows:

a) It proposes a new test which may be applied to infer whether asset price predictability is the result of non-synchronous trading or other sources of delayed price adjustment;
b) It explores the link between the seasonality of volatility and "unjustified" price movements. It thus proposes an innovative way in which one may pinpoint excessive volatility in the absence of data about dividend expectations;
c) It adds new empirical evidence on the efficacy of call auctions suggesting that the expected theoretical benefits of auctions may not always materialise, giving reasons why this may be the case;
d) It investigates the microstructure of a trading setup in an emerging market, when most research has up to now focused on established markets;
e) It presents new empirical evidence on the January effect and Monday effect in stock market data; and
f) The thesis puts forward practical suggestions to be considered by market designers which may enhance pricing efficiency.

CHAPTER 2:

STOCK MARKET MICROSTRUCTURE: A REVIEW OF SALIENT LITERATURE

2.1 Introduction

The increased availability of detailed stock market data enabled researchers to investigate financial trading in more detail than was previously possible. Classical economics predicts price formation to be a function of demand and supply. Whilst there are fundamental truths in this theory, it is mainly applicable in a setting in which an equilibrium price can be established. Trading sequences may be thought of as a process with the ultimate aim of establishing the "equilibrium price" of a financial asset – and market microstructure is concerned with studying the latter process which classical economics tended to take for granted. In practice demand or supply may be unusually low or high at a particular point in time, and in such cases the equilibrium demand-supply approach may be too simplistic a model of price determination. Different trading structures are designed to minimize the adverse impact of such temporary fluctuations, and this partly explains some of the theoretical findings discussed below, that market structure can affect the pricing process – at least in the short term.

Market microstructure studies investigate the trading and the pricing processes, and the behaviour of market participants with particular reference to how they react to asymmetric information. The ultimate aim is to detect possible relationships between such factors, and perhaps propose better trading structures and policies. Given that trading systems vary from one exchange to the other, researchers often argue that findings cannot usually be generalised across markets. It is the aim of this chapter to outline the basic features that are commonly witnessed in a cross-section of markets, and the main explanations that have been proposed to account for such characteristics. Thus, the chapter describes the different types of market participants, trading orders and trading system types. The approaches of the inventory and information-based models as explanations of the bid-ask spread are summarised, and typical features such as volatility variations across the trading day are described.

Information is a central concept in market microstructure studies, and it may be considered as the interlinking idea throughout this chapter. Whilst the initial market microstructure models tended to abstract from the concept of information, the latter has now gained a fundamental role in the area. Indeed, most of the concepts discussed in this chapter, may be linked to the notion of how information affects security prices. For instance, theoretical models of market microstructure usually feature an informed trader who avails himself of inside information to trade profitably. This notion may influence the types of orders submitted on the market, given that limit orders submitted by uninformed traders may be "picked off" by informed ones who trade profitably. Asymmetric information models predict that the bid-ask spread is affected by the perceived degree of inside information available to particular traders. Similarly, the higher spreads at the beginning of the trading day may be explained by the notion that information asymmetry is typically higher at the opening, following the overnight trading break. Trading volumes (and therefore liquidity) may be responsive to new information on the market. Information provision is thus an important consideration which is taken into account when designing trading setups. This explains why market designers devote attention to market transparency, in terms of the promptness of information disclosure, and which kinds of information should be disclosed (such as unfilled order data).

This chapter constitutes a brief description of basic market microstructure ideas – more detailed literature accounts relating to the specific areas tackled in this dissertation are shown in the empirical chapters themselves. The chapter is organised as follows. Section 2.2 contains an outline of the main issues that have been tackled in market microstructure. Given that exchanges are continuously automating their operations, and a number of exchanges and electronic communication networks (ECNs), are increasingly converging to a limit order book form of trading, the concept of limit order trading is also discussed. Section 2.3 of the literature review presents a brief account of the multi-dimensional concept of liquidity and how various authors have quantified liquidity in the finance discipline. Section 2.4 concludes.

2.2 Brief Overview of Market Microstructure Issues

2.2.1 A Basic Framework

Market microstructure models endeavour to explain a mixture of issues pertaining to the trading process. Most market microstructure models are constructed through the predicted behaviour of three kinds of participants described below.

- *Liquidity traders* enter the market because they have surplus cash to invest or they may require currency and therefore sell their assets. Such traders submit their orders to brokers, who then forward these instructions to the trading system or to the appropriate exchange officials. It is expected that over time, the random patterns of liquidity traders cancel out, and therefore liquidity trading is not usually associated with any long-term price movements.
- *Informed traders* have access to inside information which is not available to the rest of the market. Given this, insiders can trade profitably on mispriced assets and it is expected that such strategic trading will result in long-term price movements reflecting this information.
- The last category of participants consists of the *market makers* who are also called specialists or dealers.[1] Market makers are assumed to facilitate the trading process and hold an inventory of the assets in which they are "making a market". They are expected to supply liquidity to the market, by quoting schedules of bid-ask prices at which they are willing to trade. Typically, the schedule will quote less favourable prices in respect of larger transactions, and this may be explained both by inventory management and asymmetric information factors as outlined in Sections 2.2.3 and 2.2.4. One main problem faced by market makers is trader anonymity – market makers are assumed not to know whether their counterparty is a liquidity trader or an informed trader. In the former case, the specialist expects to make a profit through the

[1] For theoretical purposes, the differences between these terms are largely immaterial, maybe except for the fact that a specialist on the New York Stock Exchange (NYSE) is the sole person in charge of the trading process for a particular security, whereas dealers on NASDAQ are not accorded such "monopolies". Specialists do not necessarily behave as monopolists given that their quotes have to compete with offers from limit order traders and their performance is supervised by exchange officials. Yet, NYSE specialists' operations were investigated in 2003, with a special emphasis on whether they use the exclusive knowledge of future order flow to their favour. Research has also questioned the fairness of the spreads quoted by dealers on NASDAQ (Christie and Schultz; 1994 and Demsetz; 1997).

bid-ask spread, while in the latter case he expects to make losses (since otherwise the informed trader would refrain from trading).

Most market microstructure models have been constructed to explain various empirical outcomes which are witnessed on real markets, through the optimal decision processes of these three building blocks.

2.2.2 Types of Orders and Trading Systems

Orders submitted by traders may include different specifications, as outlined by Teweles and Bradley (1998; pp. 154-169). One basic choice faced by traders is whether to specify a price at which they are prepared to trade, or to submit an order that transacts "at the going prices". In the former case traders would be submitting limit orders, while in the latter case they are submitting market orders. In both cases, traders specify the amount which they are willing to transact.[2] Trading through limit orders is expected to result in more favourable trading terms, given that the trader might be able to transact at a price which is slightly more favourable than the prevailing one, if the limit order enables her to take advantage of short-term price movements. However, while a market order may be executed immediately by trading against the best prevailing offers, a limit order may have to wait prior to execution; indeed limit orders may end up unexecuted. Besides, a limit order may also be considered as a "free option" submitted to the market at large, which will only execute when it is favourable to the counterparty, as discussed in Section 2.2.8.

The differences between limit and market orders also imply that limit order traders are patient traders who are providing liquidity to the markets by making offers to trade. Conversely, market order traders are "impatient" and they consume the liquidity which is available on the market.[3] At times, the idea that limit order traders provide liquidity to the market is questioned, as these orders frequently get cancelled when prices move towards the specified

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[2] Some types of orders also allow traders to submit "flexible" quantities, usually depending on the going market price.

[3] Foucault, Kadan, and Kandel (2005) argued that patient traders may include institutions or long-term investors whose original intention was to invest in the security for a long period of time. Impatient traders may be arbitrageurs who trade on temporary price differentials, and brokers who have to watch out against adverse price movements which impact on the prices they obtain for their clients.

limit price.[4] In addition, one should not rely on limit order traders as a liquidity source in exceptional circumstances such as the October 1997 New York Stock Exchange (NYSE) market crash. For example, through an empirical investigation, Goldstein and Kavajecz (2000) noted that limit order traders largely withdrew their liquidity supply on the day following the crash.

The limit order book is a collection of limit orders submitted by the traders who intend to transact different securities. Limit orders accumulated in the book trade against incoming market orders or, at times, match with limit orders on the opposite side of the market. Limit orders are selected for trade through pre-established priority rules. The first limit orders which are executed are those with the maximum price priority, i.e. those with the highest bid prices and the lowest ask prices. Multiple orders with the same limit price are then prioritised according to the time at which they were submitted, the earliest orders getting the highest time priority.[5]

The trading systems of most stock exchanges are a mixture of order-driven and quote driven processes. In pure quote driven markets, such as the NASDAQ system up to the early 1990s, transactions occur on the basis of the quotes supplied by market makers, which are the main source of liquidity. In contrast, order driven markets such as the Tokyo Stock Exchange, and ECNs such as Island and Instinet depend on limit orders as a source of liquidity.[6] Other markets rely on both liquidity sources, notably the "hybrid markets" NYSE and AMEX. For instance, on NYSE small orders are processed through the limit order book, while larger orders entail a more active role on part of market makers.

One main disadvantage of a pure limit order book trading system is that it depends on public limit orders for liquidity, which may not always be forthcoming – especially in the case of smaller stocks. A lower degree of liquidity may translate into higher temporary volatility, as prices become more vulnerable to liquidity shocks. Foucault, Kadan and Kandel (2005), used a dynamic model of the limit order book and predicted that introducing a market maker in such a system, enhances competition among liquidity providers, when the ratio of liquidity providers to total traders is small. A further disadvantage of a limit order book trading system

[4] For example Hasbrouck and Saar (2002) found that on Island ECN, more than a quarter of the submitted limit orders are withdrawn unexecuted within two seconds. Similar concerns were also stated by Hasbrouck (undated).
[5] Orders may be revised or cancelled at any time prior to execution; however they might lose time priority upon a revision. When an order is partially executed, the unfilled portion does not usually lose its time priority.
[6] As pointed out by Coppejans, Domowitz and Madhavan (2001), one should not assume a total absence of market making activities in "pure" limit order systems. The anonymity of these systems implies that anyone who is willing to undertake market making activity can do so, despite not being officially identified as a market maker.

is that the execution of large trades (blocks) usually requires some form of human interaction or some kind of prior arrangements given that otherwise the share price may fall drastically as a large number of shares get "dumped" on the market. Despite this, one should also note that an electronic trading process such as a limit order book is likely to lower trading costs, as empirically outlined by Domowitz (2002).

2.2.3 Inventory Control Models

Inventory control models, such as the theoretical studies of Garman (1976), Stoll (1978) and Amihud and Mendelson (1980), tend to view the spread as the market maker's compensation for holding a level of inventory which deviates from his desired holding. Therefore larger transactions are associated with higher spreads, given that they result in larger deviations from the market maker's optimal holdings. In such models, the position of the spread may be adjusted up or down, so that the specialist encourages trades on one particular side of the market, in order to avoid diverting excessively from his optimal inventory position. Overall, such models envisage the liquidity supplier as a trader who is better equipped to take on the risks inherent in liquidity supply, given that he holds a diversified portfolio of securities which minimizes his overall risk profile. While inventory control models can explain some categories of movements in the spread, it is generally accepted that this class of models tends to abstract from the possibility of asymmetric information. Indeed, authors such as Madhavan and Smidt (1991) who used NYSE data for a Bayesian model of the specialists' quoting process, showed that evidence of inventory control costs is not particularly strong.

2.2.4 Asymmetric Information Models

Bagehot (1971) suggested that market makers are faced with liquidity-motivated transactions and transactions based on inside information. Glosten and Milgrom (1985) developed an econometric model showing that due to the possibility of informed trading, the dealer revises his quotes downwards (upwards) after satisfying a sell (buy) order. This results in the time series of transaction prices following a martingale.[7]

Kyle (1985), in a sequential auction model, showed that the trading strategy of the insider partly depends on the variance of the uninformed order flow, given that the latter is a source through which the informed trader can hide his strategic trading. The market makers adjust prices by some proportion of the observed total order flow. Thus:

$$\tilde{p} - p_0 = \lambda\,(\tilde{x}+\tilde{\mu}) \qquad (2.1)$$

where $\tilde{p} - p_0$ is the price adjustment, $\tilde{x}$ is the informed order flow and $\tilde{\mu}$ is the uninformed order flow. The larger λ is, the smaller the depth of the market, given that the adjustment for a given order flow will be higher. A further insight as to how market makers adjust quotes is found in the empirical studies of Lee, Mucklow and Ready (1993) and Kavajecz (1999) who suggested that specialists actively manage both the prices they quote as well as the depth committed on their schedules. Easley and O'Hara (1992a) developed a theoretical model and showed through simulations that higher volumes may slow the adjustment towards efficient prices, on the grounds that it would be more difficult for the market maker to distinguish between informed and uninformed order flow.

Easley and O'Hara (1987) argued that if informed traders always profit on their trades, they would prefer to trade in larger quantities. Given this, the market maker will assume that larger transactions are more likely to be informed and she sets a higher spread for large transactions. Similarly, the market maker will adjust her price expectations by a larger amount, after witnessing a large trade and this partly explains the price drops observed after large scale sales of stock. The authors developed an econometric model showing that order flow patterns can be a source through which market makers adjust their beliefs about the probability of informed trading, and therefore the spread. In this way, prices follow a martingale but they are not Markov (i.e. the future movement partly depends on the history of prices rather than simply on the current value).

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[7] A martingale is a stochastic process which is weaker than a random walk. The random walk model requires uncorrelated price changes, yet a martingale process allows for possible serial dependence in the series. The main requirement of a martingale process is that the expected future value of an asset, given all available information is the current value i.e. $E(P_{t+1} \mid \Phi_t) = P_t$, where Φ_t is current information which contains at least the past history of P_t. This results in, at least, semi-strong efficiency, where market prices reflect all publicly available information. A martingale process allows for dependency in higher conditional moments of the price changes, such as the conditional variance. The latter is an empirical feature of financial markets, which often shift in between high volatility periods, and low volatility ones.

Admati and Pfleiderer (1988) categorized uninformed traders into non-discretionary and discretionary liquidity traders. In their econometric model, the latter category of traders choose the time of the day during which to trade and take account of the possible strategies of informed traders. Discretionary liquidity traders choose the lowest cost period in which to transact, and this is the period with the highest uninformed trade variance and lowest λ. Thus discretionary uninformed traders transact together in one particular period. In mimicking uninformed order flow, informed traders transact comparatively more in this particular period and therefore they amplify this pattern. This may explain the volume clustering patterns observed during trading days, however, it does not explain why clustering tends to occur at the beginning and closing of the trading days.

In some practical circumstances, market makers might be able to distinguish between informed and uninformed order flow. For example, a specialist might ask a broker about the identity of the ultimate trader or the motives behind the transaction. Forster and George (1992) and Benveniste, Marcus, and Wilhelm (1992) model a situation where market makers can partially distinguish between informed and uninformed trading. Both studies predict a reduction in trading costs for uninformed traders. This may draw more uninformed trading to the market, resulting in a lower overall spread as compared to the completely anonymous trading framework.

2.2.5 Sources of the Bid-Ask Spread

Demsetz (1968) developed the idea that the immediacy of transacting has a cost and therefore specialists require a compensation for providing liquidity – the spread. He argued that active securities have lower spreads, partly because the competition between limit order traders is fiercer, given that the shorter expected waiting time to execution encourages traders to submit more limit orders. Copeland and Galai (1983) built a theoretical model which viewed the dealer's quotes as two options provided to (informed) traders – one option to buy and another to sell stock. The spread reflects the value of these options.

Madhavan (1992), constructed a theoretical model, and amongst his predictions, he showed that when decomposing volume, one may detect different effects on the bid ask spread. The latter tends to be positively correlated to transaction size but negatively correlated to transaction frequency.

Tinic (1972) empirically found that the bid ask spread is positively correlated to price of the stock, and the level of trading concentration on NYSE, and negatively correlated to the continuity and extent of trading activity. Similarly, Roll (1984) empirically showed that the calculated bid ask spread is strongly negatively correlated to firm size. This is in line with the fact that larger firms attract larger volumes of trading, resulting in lower trading costs. In addition, Roll theoretically showed that jumps in between the bid and the ask induce negative serial correlation in time series of transaction price changes.

Various empirical studies such as McInish and Wood (1992) and Chung, Van Ness and Van Ness (1999) found that the spread follows a U-shaped pattern throughout the trading day. Such a pattern has been attributed to inventory effects, asymmetric information effects as well as specialist market power, where dealers try to trade on their superior knowledge of order flow.[8]

In their empirical analyses, Glosten and Harris (1988), Hasbrouck (1988) and Madhavan and Smidt (1991) distinguished between the information component of the spread and other components such as order processing costs, specialist monopoly power and inventory components. One possible distinction criteria for doing this, is that information-related effects tend to cause permanent price changes whereas the other components only lead to temporary price changes. Such studies indicate that the asymmetric information component of the spread is more significant than the other factors.

Amihud and Mendelson (1986) theoretically and empirically investigated the relation between spreads and expected returns. They showed that assets with higher spreads yield higher expected returns, and therefore investors with a long enough holding period, tend to favour assets with higher spreads. The finding that long-term investors (rather than short term ones) tend to prefer high-spread assets, may be explained by the fact that the former can amortise their trading costs over a longer holding period and in addition, the low liquidity of high spread assets makes them an unfavourable choice among short-term investors. The authors noted that these effects are consistent with market efficiency, and the results imply that companies may reduce their cost of capital by improving the liquidity of their shares. These findings were subsequently questioned by Eleswarapu and Reinganum (1993) who empirically showed that the return premium associated with the spread follows a seasonal pattern.

[8] See Stoll and Whaley (1990).

2.2.6 Short-Run Price Patterns

Wood, McInish and Ord (1985) examined one minute interval returns for NYSE equities and noted defined patterns. There is a tendency for higher returns and standard deviations during the opening and closing of the trading day. The standard deviations of returns tend to be U-shaped across the day, and they are thicker in the initial period. Large price changes also tend to happen after larger no trade intervals. Such time series patterns tend to cast doubts on models which assume independent identically distributed price changes, such as random walk processes.

Harris (1991) empirically showed that observed prices on various US markets tend to cluster on even-eights, and a possible reason for this is that traders use discrete price sets (e.g. based on quarters, halves or whole numbers) to simplify their negotiation process. Further evidence on price clustering was garnered from other markets, including derivative contracts e.g. McGroarty, Thomas and ap Gwilym (2005). The latter study focused on Euronext-LIFFE short-term interest rate futures and suggested that price clustering may account for a substantial portion of the bid-ask spread. Similar results were obtained by McGroarty, ap Gwilym and Thomas (2004) in the context of foreign exchange market spreads.

Kraus and Stoll (1972) empirically studied block trading in stocks by institutional investors, and noted that the price effect of blocks which trade on plus ticks (buys) is mostly of a long-term nature, while price effects of blocks which trade on minus ticks (sales) tend to be transitory. This difference has been explained by the fact that the specialist does not typically go short to accommodate a large purchase, and therefore his participation in the transaction will be less significant and in this way he has a lower incentive to negotiate a price away from equilibrium. An alternative explanation as noted by Chan and Lakonishok (1995) is that buyer-initiated trades have a larger probability of being informative, given that there are many liquidity-related reasons to sell, but not as many to buy. In the latter empirical study, the authors noted that the price impact of large trades is significantly related to the identity of the transacting fund management firm, which may be attributed both to the differing immediacy demands across fund managers, and to the possibility that some particular fund managers are more likely to be perceived as being informed.

Hausman, Lo and MacKinlay (1992) using an ordered probit model, found that the sequence of trades affects the conditional distribution of price changes, especially for the larger stocks and the more active ones. Larger trades tend to have larger price impacts, and the magnitude of the price movement is affected by the sequence of past price changes, and whether orders were buyer or seller initiated.[9] The authors showed that price discreteness is useful in explaining price changes and they found that prices tend to revert in between transactions. The latter effect in their sample was higher than may be explained by prices bouncing between the bid and the ask.

Easley, Kiefer and O'Hara (1997) and Easley, Engle, O'Hara and Wu (2002) showed that order flow and trade patterns are an important complementary source of information.[10] In particular, one may argue that a prolonged period where no orders are submitted to the market may signal some sort of information, as suggested by the theoretical models of Diamond and Verrecchia (1987) and Easley and O'Hara (1992b).

2.2.7 Market Design

Trading mechanisms function in order to satisfy the demand and supply of financial assets, first and foremost through establishing prices. Given that market mechanisms vary in terms of the timing at which transactions may occur, the role of dealers (if any), the types of orders that may be submitted, minimum price variations and the information dissemination processes, the pricing process varies in between settings as well. In this way trading mechanisms can affect transitory price behaviour and market liquidity. The idea that market structure can affect the pricing process has been investigated since Demsetz (1968), who suggested that factors such as the number of traders can affect the spread. Theoretical models of market design include Garbade and Silber (1979), Ho and Stoll (1983), Madhavan (1992) and Glosten (1994). Detailed discussions of the findings of these models are beyond the scope of this analysis, however one should note that different trading systems tend to have both good points and limitations. In this way, the "optimum" trading system for a given market is likely to be a

[9] Lee and Ready (1991) developed an algorithm to distinguish between buyer and seller initiated trades. Transactions are classified according to the direction in which they deviate from the prevailing mid-quote. Trades executing at the mid-quote, are classified using a tick-test. An alternative methodology was proposed by Ellis, Michaely, and O'Hara (2000).

[10] In both studies, the authors specified an econometric model and subsequently presented an empirical application.

complex decision, which partly depends on market designers' objectives which often prove to be conflicting, as noted by O'Hara (1995; Chapter 9).

Empirical investigations of different trading systems include Tinic and West (1974), Amihud and Mendelson (1987), Lee (1993), Jegadeesh (1993), Christie and Huang (1994), Christie and Schultz (1994), Chang, Hsu, Huang and Ghon Rhee (1999), Chung, Van Ness, and Van Ness (2001) and Huang (2002). Again, one should note that such empirical comparisons usually cannot be generalised across markets given that different venues trade different assets under different conditions.

2.2.8 Limit Order Trading

Trading systems for financial assets such as equities, bonds and foreign exchange, have become increasingly automated during the twentieth century. In cases such as the Tokyo Stock Exchange, and various Electronic Communication Networks (ECNs) such as Island, this means that the system has become totally order-driven, with virtually no inbuilt liquidity-enhancing functions such as market makers, dealers or specialists. Such frameworks completely function as limit order books. Other exchanges with inbuilt market making functions such as NYSE and AMEX, still allow limit order trading. In the latter settings the limit order book may be thought of as part of a larger trading system having different liquidity enhancing features.

Order driven systems, although conceptually simple frameworks, may differ in the way they are be structured. For example, market orders might be submitted and they trade against the best prevailing limit orders on the other side of the market. Other systems, such as the Stock Exchange of Hong Kong (SEHK), only provide for the submission of limit orders, and therefore when a trader submits a market order to her broker, the latter will have to set a "target price", so that the instructions are forwarded as a limit order. A sufficiently large market order typically "moves along the book", which means that if the order is larger than the number of securities available for trading at the current best offer, the remaining part of the order transacts at the next best offer. This goes on until all the order is executed. In other systems such as the (former) Paris Bourse, the unexecuted portion of the market order is converted to a limit order at the price prevailing for the executed portion.

Limit order traders enhance liquidity on the market, since their orders constitute offers to trade instantaneously at a given price. One way in which dealers' quotes and limit orders differ as sources of liquidity, is that in the former case, it is reasonable to assume that quotes are adjusted on a regular basis, depending on the new flow of information and inventory positions. On the other hand, not all limit order traders can monitor their orders continuously, and in addition the cancellation of a limit order may take several minutes to effect, once it reaches the broker. Therefore, prices could be less flexible in case of limit orders. Jang and Venkatesh (1991) found that actual quote revisions on NYSE are different from what would be predicted by market microstructure theory, and they attributed this to the fact that quotes from the limit order book are updated less frequently.

The above "inflexibility" is related to the "free option" property of limit orders. The latter concept refers to the fact that a limit order trader is providing an option to other market participants to transact a given quantity of stock at a specific price.[11] This option may eventually go in the money, as the expected value of the stock changes, and when this happens, the limit order trader will transact at a negative expected profit unless he withdraws his order. This may lead to inferior performance for limit orders. Given that limit order traders may end up providing a free "in the money option" to the market, Glosten (1994) argued that the monitoring cost of limit orders should be considered when estimating trading costs.

Following an empirical analysis of large limit orders on the European Options Exchange (EOE), Berkman (1996) argued that there is a larger tendency for limit order traders to lose to informed traders, at the arrival of new information and when the limit order traders do not monitor their quotes frequently. In addition, the longer the waiting time for execution of a limit order, the higher the probability that the order will be "picked off". This means that the limit order trades against an order which was submitted by a trader with superior information, including new public announcements which were not yet available at the time that the limit order was submitted. This is partly confirmed by Anand and Martell (2001) who found that for their sample of buy limit orders, the longer the waiting time, the worse the performance of the order. However, for sell orders the reverse was true: the longer the waiting time, the better the performance.

[11] Copeland and Galai (1983) used this "option concept" to analyse the quotes provided by market makers.

One way in which the risk of having limit orders "picked off" can be minimized is to mark up (down) the order prices in response to positive (negative) public announcements. Such "indexed limit orders" were described by Black (1995) and algebraically modelled by Brown and Holden (2002). The possibility of the limit order being "picked off" may also be reduced if the order provides for its own cancellation after a specified period.

Jarnecic and McInish (1997) empirically calculated the option value provided by limit orders on the Australian Stock Exchange, and found that the option value is higher in case of both the less liquid and the most liquid stocks. The higher option value for the former is explained by the fact that less liquid stocks tend to be more volatile and option pricing models predict that option values increase as the underlying volatility increases. The higher option value for limit orders on most liquid stocks is due to the fact that the latter assets exhibit lower spreads, and therefore limit order traders would have to specify a more competitive limit price for their orders.

The value of the "free option" provided by limit order traders is also dependent on the degree of transparency in the market. For instance, Madhavan, Porter and Weaver (2005), examined a change in transparency policy on the Toronto Stock Exchange, when the latter publicly disseminated the limit order book on both the traditional floor and on its automated trading system. The authors reported a reduction in liquidity following the increased transparency, and this was attributed to an increase in the "free option" cost of limit-orders, resulting in limit order withdrawals. The authors also found an increase in execution costs and volatility after the increase in transparency. These results were partly confirmed by Boehmer, Saar and Yu (2005), who analysed increased pre-trade transparency on the NYSE. The authors reported that traders tended to submit smaller limit orders and an increased tendency for limit orders to get cancelled. Despite this, the authors still reported higher overall liquidity following increased transparency, and a pronounced tendency towards limit order trading.

Bloomfield, O'Hara and Saar (2005), after conducting an experimental study, argued that one important factor in the liquidity generating process of electronic markets is the submission of limit orders on part of informed traders. During the initial periods of the day, when mispricings tend to be higher, informed traders tend to submit market orders so that they "pick off" limit orders – in this way informed traders initially consume liquidity. Later on during the day, informed traders shift to a limit order strategy. The authors also confirmed that uninformed traders tend to follow an opposite pattern, i.e. they start by submitting limit orders and then trade through market orders in order to reach their targets. The authors concluded that such processes enable electronic markets to generate liquidity, even when the information process is asymmetric.

2.3 Measuring Liquidity

One important question that persistently crops up in academic literature relates to the measurement (and at times the definition) of liquidity.

Kyle (1985) argued that there are different dimensions to liquidity, namely:

- Tightness: the cost of liquidating a position over a short period of time;
- Depth: whether shares may be transacted with minimal price impact; and
- Resiliency: the swiftness at which prices converge to their fundamental values.

Given these different facets of liquidity, empirical studies used different measures of liquidity, some of which are described below.

The most commonly used liquidity measure since Demsetz (1968), was the bid-ask spread, given that this is the market maker's compensation for supplying liquidity. From a trader's point of view, the spread determines the fee that he pays for the ability to transact shares promptly and therefore the higher the spread, the lower the liquidity. Despite this, the spread often proves to be an imprecise measure of transaction costs given that a portion of market orders execute against limit orders and therefore trade at more favourable prices. Conversely, large transactions often execute at prices beyond the spread.

A second related measure of liquidity is market depth, in terms of the amount of shares available at each bid and ask price. In this way, reductions in liquidity may occur through a decrease in depth even if the quoted or effective spreads remain unchanged.

Another measure of liquidity is trading frequency i.e. the number of trades which are executed in a specific time interval, irrespective of trade size. The relevance of trading frequency to liquidity was mentioned by Demsetz (1968), whereby a higher frequency is an indicator of higher liquidity. Despite this, as pointed out by Jones, Kaul and Lipson (1994) a higher trading frequency may also be associated with higher volatility (and therefore lower liquidity).

Elyasiani, Hauster, and Lauterbach (2000), in an empirical investigation of the impacts of changing the listing venue from NASDAQ to NYSE or AMEX, used five liquidity measures as shown below:

a) The percentage bid-ask spread, calculated as:

$$\%spread = \left[\frac{(ask - bid)}{(ask + bid)/2}\right] \times 100 \qquad (2.2)$$

This measure accounts for the fact that absolute spreads are positively related to the price of the security. Thus, higher spreads might prevail due to higher overall stock prices, rather than due to low liquidity.

b) The volume of trade in the stock, i.e. the dollar amount and / or number of transacted shares.

c) The volume divided by absolute return, which is an estimate of how much volume causes a one cent change in stock price. This measure is thus related to Kyle's λ (Equation 2.1).

d) The standard deviation of the pricing error – σ_s – as defined by Hasbrouck (1993). The pricing error s, is the difference between the actual transaction price and the fundamental value. An approximation for the latter may be the random walk component of the price, following the assumption that efficient prices follow a random walk. Thus, this liquidity measure relates to the market's ability to price assets efficiently.

e) The non-systematic variance of stock returns. This is related to the market model:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \qquad (2.3)$$

$R_{i,t}$ the return of stock i on day t, is explained as a function of a constant α_i, the market return $R_{m,t}$, and a residual error $\varepsilon_{i,t}$. The authors used the variance of $\varepsilon_{i,t}$ as a measure of noise. The authors noted that while the above five measures tended to be consistent in signalling improved liquidity, researchers may still detect different patterns and information if they consider more than one measure.

Ngugi, Murinde and Green (2002), in an empirical investigation of market microstructure changes on the Nairobi Stock Exchange, cited the following four liquidity measures applicable to emerging markets:

a) The ratio of value traded to market capitalisation;

b) The bid-ask spread;

c) Trading volume; and

d) The ratio of trading volume to the sum of squared price changes. This measure adjusts the trading volume in respect of the volatility. Chang, Hsu, Huang and Ghon Rhee (1999) used this measure when comparing the liquidity of two different trading methods on the Taiwan Stock Exchange, on the grounds that these regimes lead to different volatilities and therefore one has to adjust for this factor when comparing the liquidity associated with different trading methods. In addition, this measure assesses the order flow size which can be absorbed by the market, without any significant price change.

2.4 Conclusion

The principal aim of this chapter was to provide a summary of the basic theoretical and empirical literature relating to market microstructure. The main models were briefly described and supplemented with references to actual market setups in various countries. More detailed accounts of the literature relating to the main topics tackled in the dissertation are found in the respective empirical chapters.

CHAPTER 3:

A DESCRIPTION OF THE EMPIRICAL SETTING AND THE DATA SET

This chapter discusses the issues relating to the organisation of the data set and it provides a background for the analysis of this data in the subsequent empirical chapters. The chapter is structured as follows: The statistical principles involved in modelling stock market data are reviewed in Section 3.1, whilst Section 3.2 includes a background to the Indian securities markets, which is the setting of this empirical research. The subsequent section provides details of those events which occurred during the sample period, and which might have affected the pricing process. Section 3.4 considers basic statistical properties of NSE data. Section 3.5 concludes.

3.1 Statistical Principles of Stock Market Data

Most econometric tools presume that data is stationary. A time series may be defined as stationary if its properties such as the mean and variance are unchanged over different sub-samples of the data set. Financial time series tend to deviate from stationarity and they often exhibit a time-changing mean and variance, as outlined by Mills (1999; pp. 37). Researchers usually avoid the application of econometric techniques to non-stationary data given that this may lead to flawed conclusions. For example, spurious regression results may be obtained (Granger and Newbold; 1974), or a high level of serial correlation may be misinterpreted as predictability.

Therefore non-stationary series are usually transformed to stationary ones, for instance by using log returns worked out as follows:

$$r_t \equiv \log(1+R_t) = \log\left[1+\left(\frac{P_t - P_{t-1}}{P_{t-1}}\right)\right] = \log\frac{P_t}{P_{t-1}} = p_t - p_{t-1} \tag{3.1}$$

where P_t is the price level, R_t is the (simple) return level, and $p_t \equiv \log P_t$. Using log returns presents inherent advantages such as modelling non-linear relationships through linear ones.

Taking the logarithms of prices does not guarantee stationarity and at times further transformations may be required. In addition, the distribution of log returns often deviates from the normal distribution. Various authors such as Fama (1965) presented empirical evidence which exposed the drawbacks of using a normal distribution to model logarithmic returns. Financial log return distributions tend to be peak-shaped (leptokurtic) and fat-tailed. This characteristic of financial log returns has been explained by patterns in the arrival of information, as well as patterns in traders' reactions to news, as discussed in Peters (1991). Dacorogna *et. al.* (2001; pp 133), in an empirical investigation of USD exchange rate returns, showed that as the frequency of the data increases (say from weekly to hourly) the tails of the distribution become fatter.

Stock markets usually go through periods of substantial volatility interspersed with other periods of lower volatility. This implies a time-changing variance of returns, as reviewed in Bollerslev, Chou, and Kroner (1992). Franses and van Dijk (2000; pp. 13-19) used stock index data to present empirical evidence of two further characteristics which are commonly evident in log returns:

a) Large negative returns are more common than large positive returns. This feature was not confirmed by Longin (1996) in an empirical analysis of US stock market data, and by Jondeau and Rockinger (2003) who studied different stock market indices. The latter authors suggested that the common "perception" that left tails are thicker than the right ones might have been cultivated by the presence of data outliers.

b) Franses and van Dijk (2000) also noted that high volatility often follows large negative returns. These authors showed that the former two features are not as clearly evident in exchange rate returns data.

The degree to which the above characteristics are evident in the sample being used throughout this dissertation, is preliminarily investigated in Section 3.4.

Stock market data present other challenges to researchers as outlined below:

a) Stock prices are usually discrete prices; for example price changes have to be in one-sixteenth of a dollar, or multiples thereof. Possible effects of price discreteness include price clustering (Harris; 1991). Such effects might still be present to some degree in price series where trading is decimalised, given that in such cases prices have to be quoted in cents and therefore they are not "continuous". According to Campbell, Lo and MacKinlay (1997; pp. 110-112), the impacts of price discreteness become more evident in case of lower-priced stocks and as the sample period shortens.

b) When analysing stock market data which span over a considerable period of time, one should be aware that the conditions which underlie the pricing process are likely to change. For example, a long sample period may include changes in the composition of stock indices and changes in company structure due to merger and takeover activity. At times changes in the trading procedures and changes in the trading hours might also be present. Dacorogna *et. al.* (2001; pp.5) refer to these effects as the "breakdown of the permanence hypothesis" and the authors also question whether a researcher can claim that he is analysing the same market when working with a long time-series.

c) Transactions occur at random times and this results in irregular sampling intervals. Most econometric techniques assume a homogeneous time series i.e. regularly spaced intervals. Thus, the researcher may have to homogenise the data sets by extracting equidistant transaction prices. When adopting such an approach, one should keep in mind that the homogenised data set is not the original one; indeed Dacorogna *et. al.* (2001; pp.2) refer to such sets as "artefacts" obtained from the actual price series.

When homogenising a data set, say by extracting hourly prices, one may find instances when the stock does not trade. If this gap is filled by inserting the previous trading price in the homogenised sample, this results in a return of zero for the particular period, and perhaps a "jump" in the return for the successive period. According to Campbell, Lo and MacKinlay (1997; pp. 84), this may induce negative serial correlation in returns, as well as bias in the moments of the return distribution. An alternative approach might be to fill the gaps through linear interpolation of the values of neighbouring observations. Yet, this might be undesirable given that such approach partly conditions the price in period t on the price in period $t+1$, when researchers usually assume that the price at time t depends on the information which is available up to that time. Nonetheless, according to Dacorogna *et. al.* (2001; pp.37), most statistical research may employ both interpolation methods.

Finally, one should note that when data are homogenised, the researcher is disregarding valuable information which may be gleaned from order flow and trading patterns. For example, Diamond and Verrechia (1987) assumed that a no-trade interval might signify the presence of unfavourable information which cannot be traded upon through short sales. As outlined in the previous chapter, several other papers have shown that order flow patterns are a relevant source of information.[12]

3.2 A Background to the Indian Financial Markets and the National Stock Exchange (NSE)

The data for this research were obtained from the National Stock Exchange of India (NSE) with the help of Dr. Joy Suppakitjarak. Financial practitioners are becoming increasingly interested in emerging markets given that these may present diversification benefits, as well as potentially higher growth rates. Researching emerging markets more thoroughly is an important prerequisite for the academic community to catch up with this increased interest. The selection of Indian stock market data is thus a step in this direction. In addition, the choice of this exchange presents the following distinct advantages:

- Throughout the sample period approximately 1,100 equities traded on NSE.[13] Such a number of securities enables a researcher to select a large sample of most liquid stocks, and this enhances the power and statistical significance of the analysis, due to a higher expected amount of observations.

- NSE provides access to a large market for shares in terms of trading volumes. Around 400,000 transactions were usually processed during a typical trading day in the sample period. Observations in the region of 500,000 transactions were also common.

- The data set is reasonably detailed. Apart from the price and volume of each trade, the set also includes high-frequency observations of the value of the main indices.

- Detailed data were available for the period March 1999 – March 2000 (both months included). This is a reasonably long period with which a researcher may conduct proficient time series and event studies. In addition, longer time series data sets relating to the main indices were available from the NSE website.[14] Tests shown in

[12] See Easley, Kiefer and O'Hara (1997), Easley and O'Hara (1992b), and Easley, Engle, O'Hara and Wu (2002).
[13] This contrasts with other emerging markets, where relatively few shares are traded.
[14] www.nse-india.com

this chapter were conducted on data from the former sample period, although the sample was extended in the empirical studies when a longer time series was required.

- India provides the potential to test the degree to which theoretical and other empirical market microstructure findings are applicable to this particular venue. Whilst research on emerging markets has been increasing, one may argue that there is still a high potential for further empirical investigations relating to Indian capital markets. Such research is even more required nowadays, given the financial market practitioners' increasing interest in India and similar countries.

3.2.1 Indian Securities Markets

A historical background to India's economy and financial system is given in Green, Manos, Murinde and Suppakitjarak (2003). Traditionally, India's economy was reliant on state policy. New share issues were controlled by the government, as per the Capital Issues (Control) Act 1947 and the Companies Act 1956. The Securities Contracts (Regulation) Act 1956 regulated secondary market trading. The Indian state traditionally restricted foreign investors from participating in stock market activity. This environment largely discouraged companies from using capital markets as a source of finance. Regulatory reform of the Indian capital markets took off in the early 1990s. The Securities and Exchange Board of India (SEBI) was established as regulator, and securities issues were liberalised.

Despite this, distinct "negative characteristics" of the Indian securities markets still remained. Such factors as listed by Shah and Sivakumar (2000), include:

a) The Indian securities markets were characterized by a high degree of insider trading, market manipulation and inadequate regulation to deal with these practices. Evidence on insider trading in India in the late 1990s and details about the problems with enforcing insider trading regulations are found in Agarwal and Singh (undated). With respect to market manipulation, NSE implemented a system of price limits which decreases the potential for such activities. In addition, the sample which was selected for the event study shown in Chapter 6 consisted of the most liquid stocks. Market manipulation tends to be a costly activity in liquid stocks. In addition, when NSE was set up in 1994, it brought about various improvements on the Indian securities markets as outlined in Section 3.2.2. These improvements included improved transparency and tighter checks to reduce the potential for market manipulation. Thus, one may state that the scope for market manipulation was higher in the early 1990's, which falls outside the sample periods used in the dissertation. Market manipulation and insider trading activities are an important issue which may be investigated in detail; yet this goes beyond the scope of the dissertation.

b) The traditionally oligopolistic structure of the Indian brokerage industry resulted in high brokerage fees. Despite this, the establishment of NSE may have contributed to a reduction in brokerage costs, resulting from a more transparent system of transacting as well as a reduction in barriers to entry for brokerage activity.

c) Traditionally Indian securities lending activities were disorganised. During the sample period, NSE was fostering initiatives with respect to securities lending in particular stocks, through the Automated Lending and Borrowing Mechanism (ALBM). Therefore, the absence of an organized securities lending function might not be a relevant drawback for the purpose of this research.

d) Up to the 1990's the Indian financial markets did not feature any organised derivatives trading system. During the sampling period, NSE was embarking on an initiative to establish derivatives activities on particular indices and stocks. This activity started on 12th June 2000, with futures trading on the Nifty Index.

e) Liquidity levels on the Indian markets might be comparatively low, and this is a recurrent characteristic on most emerging markets. Stocks with low liquidity levels may be more likely to feature price inefficiencies, and this may lead to flawed inferences, for instance when conducting event studies. This possibility is minimised in the dissertation by focusing on a sample of the most liquid stocks. On the positive side, this feature presents a potential to select a cross-selection of stocks of varying liquidity; for instance in Chapter 6 the effect of a call auction suspension is analysed across stocks with varying liquidity.

f) Indian capital markets also suffered from inadequate settlement systems. Despite this, NSE's weekly settlement system in force during the sample period was relatively effective, as compared to those of other Indian exchanges.[15] Towards the end of the sample period a number of (dematerialised) shares started to trade on a rolling settlement basis.

Up to the end of the sample period, India still restricted the access of capital markets to foreign investors, both through controls on the absolute investment amount, and through capital gains taxes. According to Shah and Sivakumar (2000), only about fifty overseas institutional investors, out of a total of 553 registered ones, were active on the markets. These restrictions might have adverse impacts on the liquidity, efficiency and volatility of the markets.[16]

3.2.2 The National Stock Exchange (NSE)

NSE is a limited liability company that was set up in 1994. NSE is one of the major Indian exchanges, together with the Bombay (Mumbai) Stock Exchange (BSE). The exchanges are regulated by SEBI. As outlined by Krishnamurti and Lim (1999), ownership, management and trading membership on NSE are separated, which overall minimizes the risks of conflicts of interest which could arise when a person acts in multiple roles. NSE activity commenced in June 1994 with the trading of debt instruments; capital market activity initiated in November 1994 and derivatives activity started in June 2000. During the year 2000, around 1,300 equities traded on NSE, through 960 brokerage firms.[17] Most major stocks are quoted on both NSE and BSE and therefore these exchanges compete both for listings and for order flow. The major indices on NSE during the sample period were NIFTY (NSE-50 Index), NIFTY Junior (Midcap-50 Index) and DEFTY Index (Dollar-denominated Nifty Index). Nifty was the main index and it included the fifty most liquid stocks, which accounted for roughly 50% of the market capitalisation in India. Nifty Junior (Midcap) included a further fifty medium-capitalisation stocks, and accounted for a further 10% of market capitalisation.

[15] During the sample period, NSE mainly followed an account period settlement, whereby trades occurring during the week were settled on Tuesdays, with the exception of Tuesday evening trades which were settled on a T+5 basis. Whilst such methods of settlement involve considerable counterparty risk, NSE required brokers to deposit margins which were partly dependent on their trading involvement. In addition, the risk of non-settlement was borne by the National Securities Clearing Corporation (NSCC) which was the legal counterparty in charge of settlement in between NSE brokers. NSCC monitored the required broker margins in real time, as the values and the volatilities of different securities changed.

[16] For example Ngugi, Murinde and Green (2002) empirically found that on the Nairobi Stock Exchange of Kenya, the entry of foreign investors lead to higher liquidity and efficiency and lower volatility.

[17] Shah and Sivakumar (2000).

Subsequently to the sample period, further indices were added, including a broader based index Nifty 500.

According to Dalal (1999), NSE's network links over 4000 terminals in 280 cities. The trading system of NSE, called NEAT (National Exchange for Automated Trading) is order-driven with no physical trading floor. Orders are matched automatically by the limit order book system, and therefore the main role of the brokers is the submission of orders and settlement of transactions on behalf of clients. Brokers have access to the best five prices prevailing for each stock and the respective quantities on offer at each price. The last traded price is also shown, together with other data. This information is displayed in real time. The trading system is anonymous and does not disclose the identity of the traders.

During the sample period the volume of a typical trading day was around 400,000 transactions. According to Shah and Sivakumar (2000) orders may be confirmed and matched within 1.5 seconds of being submitted to the system. On average, the system handles 1,000 trades per minute, although this may go up to 6,000 orders per minute in peak times – such as the end of the trading day. According to Shah and Sivakumar (2000), this level of intensity is one of the highest in the world – for example the average intensity on NYSE is 1,300 trades per minute.

The electronic system functions as a continuous pure limit order book market. During the initial months of the sample period, opening and closing call auctions were also held. Time and price priorities apply to incoming orders. Any unexecuted orders (or parts thereof) remain on the book until cancelled or executed. Unexecuted orders may be cancelled at any time, yet trades cannot usually be cancelled.

Different kinds of orders may be submitted and these include "minimum fill", "all or none", "immediate or cancel", "good till day", "good till date" and "good till cancelled". Orders may also allow for undisclosed portions, however there is a minimum disclosed quantity specification of 10% of the total order. "Good till cancelled" orders are cancelled by the system after seven calendar days. A minimum tick size is also specified by the exchange, and during the sample period this was Rs. 0.05.

Negotiated trades taking place off the system during trading hours are to be reported to the system within 15 minutes. Those effected outside trading hours should be reported on the subsequent trading day. Negotiated trades are then reported to the market at large. A minimum trading quantity of 10,000 shares applies for these negotiated trades. Off-market deals were no longer permitted in case of dematerialised stocks as from 30th September 1999.

As a newly established exchange, NSE initiated various changes on the Indian securities market, including enhanced transparency, the risk management of broker defaults and more efficient settlement procedures. Traditionally, fake trades accompanied by false share certificates constituted a problem in Indian securities trading. In 1998, NSE began to verify trading orders, and therefore one may be confident that the chosen sample period is of sufficient reliability. During this sample period, dematerialized trading in various securities was introduced, and this should have controlled the problem of fake trades to an even higher extent. Yet, some instances of false trades still persisted after the sample period.

3.2.3 Market Wide Circuit Breakers and Price Bands

At the time of writing, India follows a system of Market Wide Circuit Breakers, which was introduced in July 2001. Following specified movements in the NSE Nifty or the BSE Sensex, equity and derivative trading activity stops throughout the country.[18] Trading resumes after a period of time, which depends on the magnitude of the movement of the index, and whether the movement occurred in the morning or in the afternoon. A more detailed description of this system is shown in Appendix 3.1.

During the sample period a system of price bands was applicable for individual stocks.[19] The objective of such bands is to reduce volatility. Daily price bands are calculated with reference to the previous day's closing price. During the sampling period, the price bands in the normal market ranged from 8% to 50%, where the lower margins applied to higher priced stocks. Price bands in the auction market ranged from 15% to 50%. Different methods of calculating price bands were applicable to illiquid securities when they failed to trade for a number of days. Orders submitted to the exchange are validated by the trading system in terms of whether they conform to price limits. This implies that the data set was "pre-filtered" to some degree for any errors, including possible typing errors by the people who input the order in the system.

[18] Trading is halted following 10%, 15% or a 20% fluctuation of the indices in either direction.
[19] This system still applies at the time of writing.

According to a descriptive account by Vaidya Nathan (2001), stock-specific circuit breakers merely served to slow down the pricing process over a number of trading days. Yet, Narasimhan (2000) specified that when SEBI reduced daily price limits in 1998, it had to reverse its decision on account of the subsequent increased volatility. The author attributed (part of) the increased volatility to higher day trading activity, facilitated by lower brokerage costs and the possibility of trading in smaller quantities following dematerialisation.

3.2.4 Borrowing of Securities and Short Sale Activity

ALBM is a system which is designed to enable brokers to borrow and lend securities, thereby assisting in short sale activity. Such activities take place during special ALBM sessions usually held on Wednesdays. The daily security price bands are applicable during these sessions as well. The closing price of the ALBM session is quoted as the weighted average of the last 30 minutes' trading prices in the session. The ALBM procedure was modified in December 1999 with the intention of making it more efficient.

Brokers indicate whether sell orders are long or short, by specifying short sales as "Open". When traders buy stock to offset short positions, the order is specified as "Close". Similarly long buys (where shares are bought without intending to take the actual delivery at the time of settlement) are specified as "Open" and "Close" when such positions are undertaken.

3.2.5 Market Timings

The sample period is characterized by frequent changes in trading hours as outlined in Appendix 3.2. [20] Trading on NSE (usually) occurs from 09:55 till 15:30. The exchange may extend trading hours if 5% or more of the users experience problems with the computer system or due to other significant reasons. The timings for the ALBM sessions were also frequently revised e.g. 14:00 – 16:00, 14:30 – 16:00, 14:30 – 16:30, 10:00 – 12:00.

[20] Changes in trading hours may alter some properties of the time series when sampled at high frequency intervals, as empirically found by ap Gwilym, Brooks, Clare and Thomas (1999) in the context of various futures contracts.

During some periods, pre-opening and post-closing call auctions were held. Pre-opening call auctions were usually held between 09:30 and 09:45, followed by continuous trading till 15:30, and subsequently by a post-closing call auction between 15:30 and 15:45. As from 9th June 1999, the initial and closing auctions were no longer held. Continuous trading was held between 10:00 and 15:30. The pre-opening and post-closing auctions were resumed on the 17th November 1999 and were suspended again, as from 18th November 1999. These changes were part of NSE's initiatives to introduce call auctions to an otherwise continuous trading system.

3.2.6 Pre-Open Algorithm

The main aim of pre-open sessions is to facilitate the establishing of appropriate opening prices, by way of "integrating" various expectations of different traders.[21] This is important when one considers that information asymmetries may be more pronounced after non-trading periods, such as the opening. Once the pre-open session is terminated, the remaining orders are considered in establishing the first price in the open (continuous trading) session.

The NSE pre-open algorithm followed the basic rule that the opening price maximises the total traded quantity. Orders which include bargain conditions such as "All-Or-None" were not considered in the pre-open. Orders could also be modified and cancelled during the pre-open session. Market buy (sell) orders were considered as orders which were prepared to trade at the highest (lowest) available price. Thus, market orders obtained the best price priority and were listed at the top of the order book in the pre-open session. The main advantage of considering market orders in the pre-open session is that a price may still be calculated in cases when limit orders specify prices that preclude any matching.

[21] A detailed review of the literature relating to pre-open sessions and call auctions is shown in Chapter 6.

3.3 Events During The Sampling Period and Their Possible Impacts on the Data

The events which took place during the sample period should be kept in mind when interpreting the empirical results of this research. Whilst the sample was filtered in order to minimize such occurrences, some remaining "noise" remains inevitable in a continuously evolving securities market. The following account of pertinent items and events was compiled after reading through the circulars issued by NSE during the sample period.

3.3.1 Dematerialisation

During the sample period, NSE was implementing a programme of securities dematerialisation. According to Shah and Sivakumar (2000), the traditional method of using share certificates as a proof of ownership led to a high rate of false trades. NSE, together with other institutions, established the National Securities Depository where ownership of securities by investors is registered. As at February 1999, just before the sampling period, institutional investors were obliged to trade around 300 securities in dematerialized format.[22] Over one half of the settlements were done electronically.[23] Trading in dematerialized format facilitated the settlement of transactions, on the grounds that shares are simply transferred in the name of the new holder, whilst a net cash settlement occurs in between brokers. Despite this, not all of the securities traded in dematerialised form as at the end of the sample period. When securities dematerialized, their minimum trading lot was usually adjusted to one unit. In case of other securities, the adjustment in delivery units was not necessarily related to dematerialisation.

3.3.2 Security Borrowing and Lending Activities

When particular shares were included in the Nifty Index or when they were dematerialised, lending and borrowing activities for such securities was usually allowed. Conversely,

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[22] NSE News, February 1999, pp.10.
[23] Shah and Sivakumar (2000).

borrowing and lending activity was discontinued during the sample period in case of other shares. These changes in borrowing and lending activities might have affected the pricing or volatility for the stocks involved.

3.3.3 Irregular Trading Sessions

A list of trading holidays throughout the sample period is given in Appendix 3.3. On the 7th November 1999, which was meant to be a national holiday, *muharat* trading was conducted from 19:00 till 20:30. This trading day was deleted from the sample in case of the event study shown in Chapter 6, given that the number of trades was less than 180,000, which is considerably lower than a typical NSE trading day. Yet, the observation was retained in the sample when using longer time series of daily data.

The timings for the trading session of Tuesday 29th February 2000 were modified "on account of the presentation of Union Budget", as specified in Circular NSE/CMTR/01482. The exchange opened at 11 a.m. and closed at 5.30 p.m. Given that market participants were advised four days beforehand of the change in trading hours, it might be reasonable to assume that the change in trading hours itself did not lead to any material changes in traders' pricing decisions, and therefore this trading day was retained in the sample.

The NSE organised additional trading sessions to test the system in a remote trading site (Pune). These sessions were deleted from the sample given that the trading flow on these abnormal sessions is probably different from that on the rest of the trading days. The sample period also includes the "new millennium" date – 1 January 2000. NSE conducted mock trading sessions in order to ensure that the computing system could handle the date transition. These mock sessions were excluded from the final sample. Months ahead of the year 2000, traders' systems were to be certified as Y2K compliant, otherwise they were disabled from operation. A contingency plan for continuity of trading following Y2K problems was also set up.

3.3.4 Other Initiatives

During the sample period, National Securities Clearing Corporation Limited occasionally changed the list of stocks which were permitted to be deposited as security by brokers. This might have affected the pricing or volatility of the stocks involved.

During the period January – March 2000, a number of securities had additional margins applicable to them i.e. brokers had to deposit additional security in respect of open positions on these stocks. These additional margins were imposed mainly in respect of outstanding positions in illiquid or highly volatile securities. This might have affected the pricing process of these securities.

Other initiatives taken during the sample period involved shortening the settlement account period and facilitating internet based trading.

3.4 Statistical Properties of the Sample

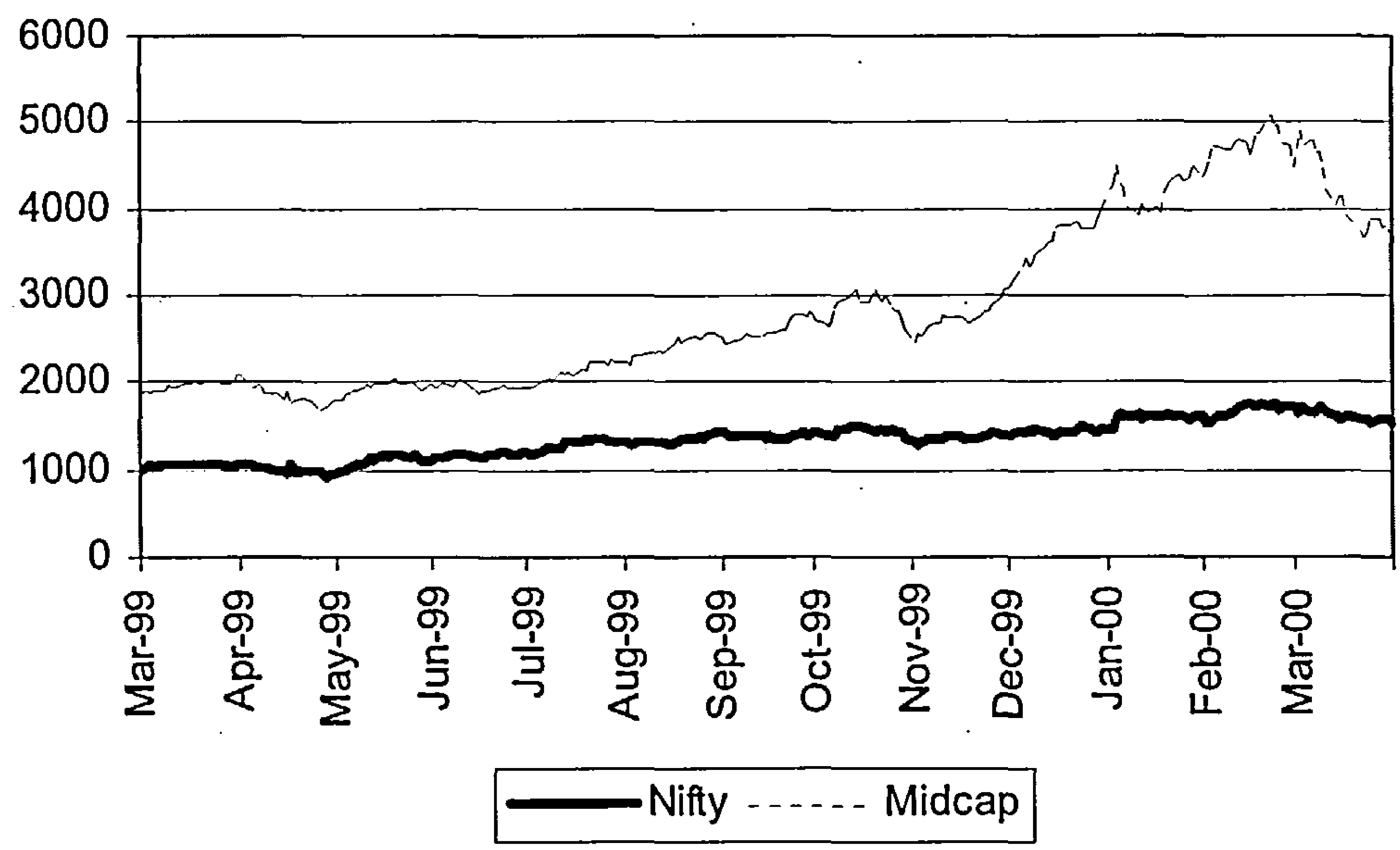
The aim of the following preliminary analysis is to inquire whether the statistical properties described in Section 3.1 are evident in the NSE indices being used for this research. The investigation uses the daily closing values of the Nifty and Midcap Indices, following the assumption that these approximate the main characteristics of the stocks traded on NSE. This study focuses on the degree to which the properties listed hereunder are evident in these indices. The hypotheses are as follows:

3.4.1 The original price series are non-stationary, however transforming the series to logarithmic returns induces stationarity;
3.4.2 Logarithmic returns are not normally distributed – they are peak-shaped and fat tailed;
3.4.3 Logarithmic returns exhibit a time-changing variance;
3.4.4 The left tail of the distribution is fatter than the right tail which implies that large negative returns are more common than large positive returns; and
3.4.5 High volatility often follows large negative returns.

3.4.1 Stationarity of the Original and Logarithmic Series

Plots of the original price series of the Nifty and Midcap 50 indices are shown in Figure 3.1. In inquiring about the stationarity properties of the data, the autocorrelation of the log returns was considered, together with the tests of Dickey and Fuller (1979).

Figure 3.1: Original Nifty and Midcap Index Data



The sample autocorrelation function of the time series x_t, at lag k is defined in Mills (1990; pp. 65) as follows:

$$\rho_k = \frac{\sum_{t=k+1}^{n}(x_t - \bar{x})(x_{t-k} - \bar{x})}{\sum_{t=1}^{n}(x_t - \bar{x})^2}, \quad k = 1,2,... \tag{3.2}$$

The standard errors of the autocorrelation coefficients were computed using the Bartlett (1946) formula, also quoted in Mills (1990; pp. 65-66):

$$S.E.(\rho_k) = \sqrt{n^{-1}(1 + 2\rho_1^2 + ... + 2\rho_{k-1}^2)} \tag{3.3}$$

where n is the number of observations.

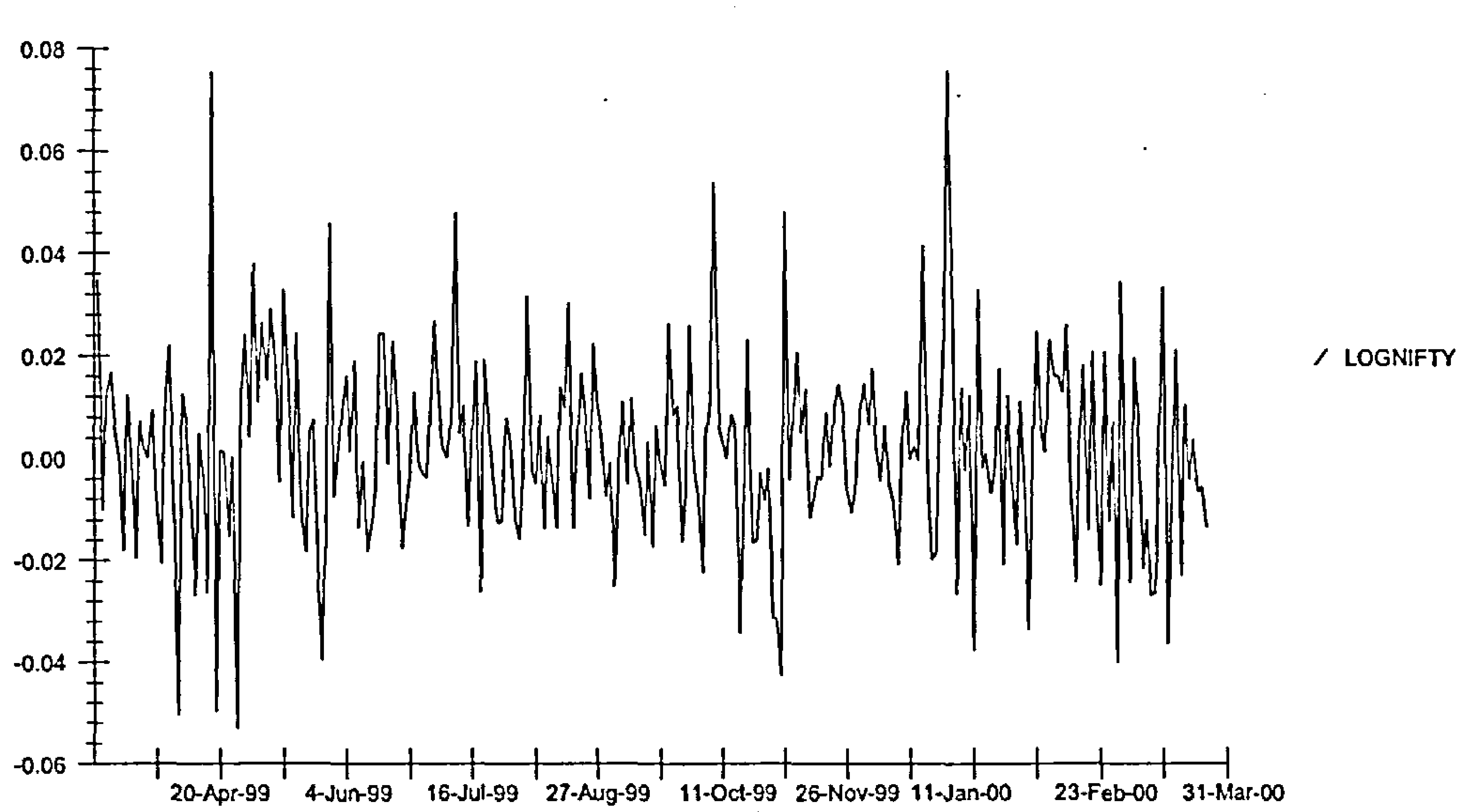
Table 3.1 shows the autocorrelation coefficients of both indices. The autocorrelation coefficients reveal a high level of serial correlation suggesting that the price levels are non-stationary.

Table 3.1: Autocorrelation Coefficients of Nifty and Midcap Indices (Levels Data – Daily Frequency)

	Nifty Index		Midcap Index	
Lag	*Autocorrelation Coefficient*	*T-ratio*	*Autocorrelation Coefficient*	*T-ratio*
1	0.98745 ***	(16.07)	0.99325 ***	(16.17)
2	0.97483 ***	(9.24)	0.98540 ***	(9.30)
3	0.96347 ***	(7.12)	0.97753 ***	(7.18)
4	0.95169 ***	(5.98)	0.96975 ***	(6.04)
5	0.93985 ***	(5.24)	0.96212 ***	(5.31)
6	0.92744 ***	(4.71)	0.95409 ***	(4.78)
7	0.91582 ***	(4.30)	0.94656 ***	(4.38)
8	0.90298 ***	(3.97)	0.93885 ***	(4.06)
9	0.89224 ***	(3.71)	0.93095 ***	(3.80)
10	0.87980 ***	(3.48)	0.92157 ***	(3.57)

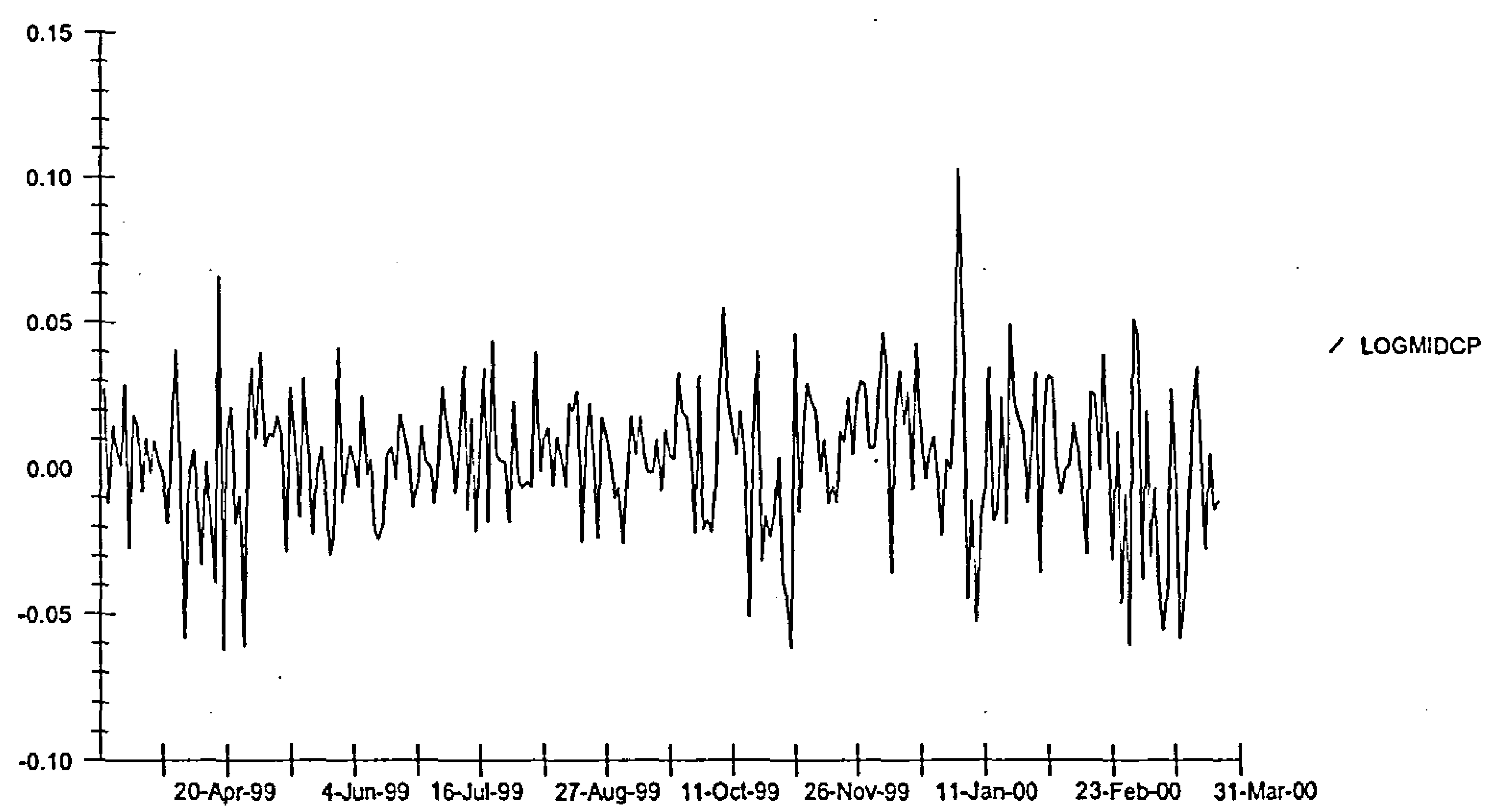
The table shows the serial correlation coefficients and respective t-ratios of the levels data up to the tenth lag. Statistical significance at the 99% level of confidence is denoted by ***.

Figure 3.2: Nifty Index Log Returns



The log return plots for both indices are shown in Figures 3.2 and 3.3 whilst the autocorrelation coefficients are shown in Table 3.2. Most of the autocorrelation coefficients are insignificant, suggesting that the log returns are stationary.

Figure 3.3: Midcap Index Log Returns



The augmented Dickey-Fuller (ADF) test was also used to confirm the stationarity properties of the levels data and log returns. The first differenced time series is expressed as a function of a constant, (an optional) trend, a lag of the levels, and n lags of the first difference. Thus:

$$\Delta x_t = f(constant,\ trend,\ x_{t-1},\ \Delta x_{t-1},\ \ldots,\ \Delta x_{t-n}) \qquad (3.4)$$

A unit root test may by formulated by comparing the coefficient of x_{t-1} with its standard error. The null hypothesis is that the series contains a unit root and is therefore non-stationary; whilst the alternative hypothesis is that the series does not have a unit root. The critical values which are used in this hypothesis test are those of Dickey and Fuller (1979).

The ADF results are shown in Table 3.3. The null hypothesis of a unit root cannot be rejected in case of the levels data, yet it may be rejected in case of the log returns series, indicating that the log prices are difference stationary.

Table 3.2: Autocorrelation Coefficients of Indices Log Returns (Daily Frequency)

	Nifty Log Returns		Midcap Log Returns	
Lag	*Autocorrelation Coefficient*	*T-Ratio*	*Autocorrelation Coefficient*	*T-Ratio*
1	-0.04486	(0.73)	0.06205	(1.01)
2	-0.06367	(1.03)	-0.01559	(0.25)
3	0.05555	(0.90)	0.03815	(0.62)
4	0.01003	(0.16)	-0.05990	(0.97)
5	0.06013	(0.97)	0.11715 *	(1.89)
6	-0.11911 *	(1.91)	-0.09017	(1.44)
7	0.05235	(0.83)	0.04293	(0.68)
8	-0.09735	(1.54)	-0.00021	(0.00)
9	0.03610	(0.57)	0.06560	(1.03)
10	0.16969 ***	(2.66)	0.17574 ***	(2.76)
11	-0.13216 **	(2.02)	-0.07240	(1.11)
12	-0.08460	(1.27)	0.00538	(0.08)
13	0.04388	(0.66)	0.13629 **	(2.07)
14	-0.00524	(0.08)	0.01751	(0.26)
15	-0.13742 **	(2.05)	-0.02303	(0.34)
16	-0.14549 **	(2.14)	-0.18520 ***	(2.77)
17	0.12306 *	(1.78)	0.03171	(0.46)
18	-0.02197	(0.31)	-0.03003	(0.44)
19	-0.03322	(0.47)	-0.04308	(0.63)
20	0.07871	(1.12)	0.05813	(0.84)

The table shows the serial correlation coefficients and respective t-ratios of log returns up to the twentieth lag. Statistical significance at the 99%, 95% and 90% level of confidence is denoted by ***, ** and * respectively.

Overall, the above tests indicate that it is reasonable to analyse the log returns series.

3.4.2 Distribution of Logarithmic Returns

The histograms of the log returns of the Nifty and Midcap Indices shown in Figures 3.4 and 3.5 seem to indicate that the data are somewhat peak-shaped, although they do not disclose strong evidence of fat-tails. Further analysis shown below, focuses on the skewness and kurtosis, and the normality tests proposed by Jarque and Bera (1980).

Table 3.3: Unit Root Augmented Dickey-Fuller Tests

NIFTY LEVELS *(Daily frequency)*		MIDCAP LEVELS *(Daily frequency)*	
Lag Length	Test Statistic	Lag Length	Test Statistic
0	-1.263	0	-0.781
1	-1.231	1	-0.858
2	-1.182	2	-0.837
3	-1.202	3	-0.834
4	-1.209	4	-0.773
5	-1.228	5	-0.852
# of Observations	260	# of Observations	260
95% Critical Value	-2.873	95% Critical Value	-2.873
LOG RETURN NIFTY *(Daily frequency)*		**LOG RETURN MIDCAP** *(Daily frequency)*	
Lag Length	Test Statistic	Lag Length	Test Statistic
0	-16.709	0	-15.030
1	-12.362	1	-11.181
2	-9.313	2	-8.800
3	-7.965	3	-8.190
4	-6.625	4	-6.388
5	-6.872	5	-6.649
# of Observations	259	# of Observations	259
95% Critical Value	-2.873	95% Critical Value	-2.873

The reported Augmented Dickey-Fuller tests assume that the time series are not trended. Augmented Dickey-Fuller tests assuming a trended time series lead to the same inferences. The null hypothesis of a unit root in the series is not rejected in case of the Nifty and Midcap price levels. The null hypothesis of a unit root is rejected in case of the Nifty and Midcap log returns.

Figure 3.4: Nifty Log Returns Histogram and Normal Distribution

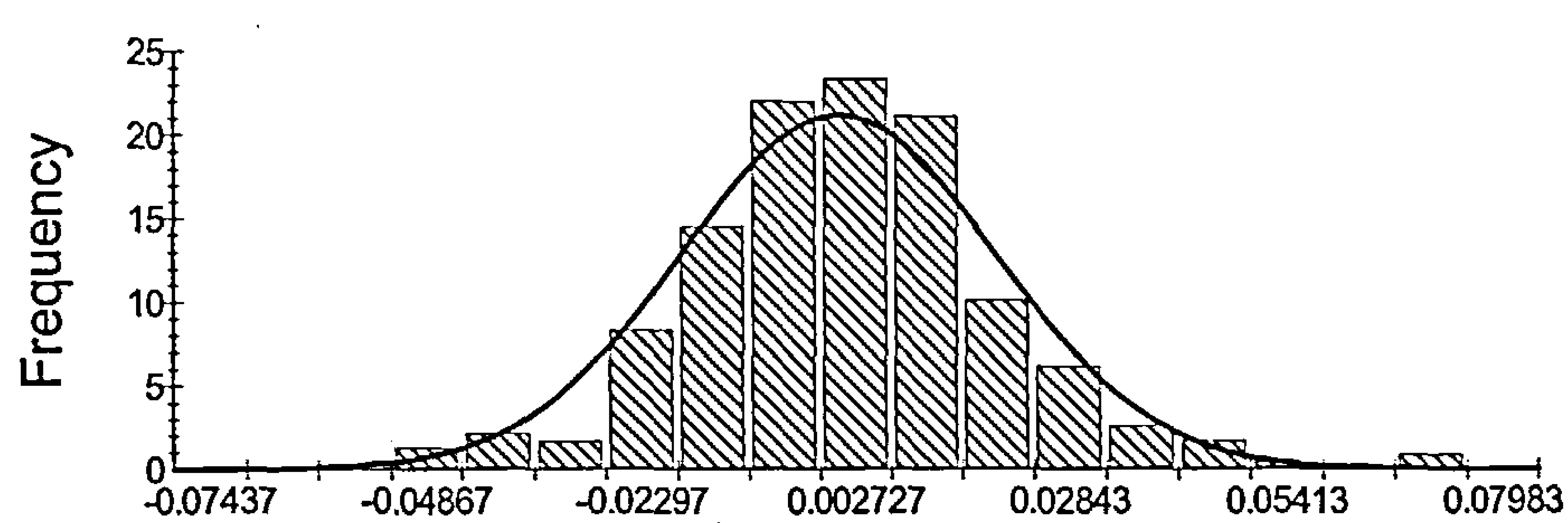


Figure 3.5: Midcap Log Returns Histogram and Normal Distribution

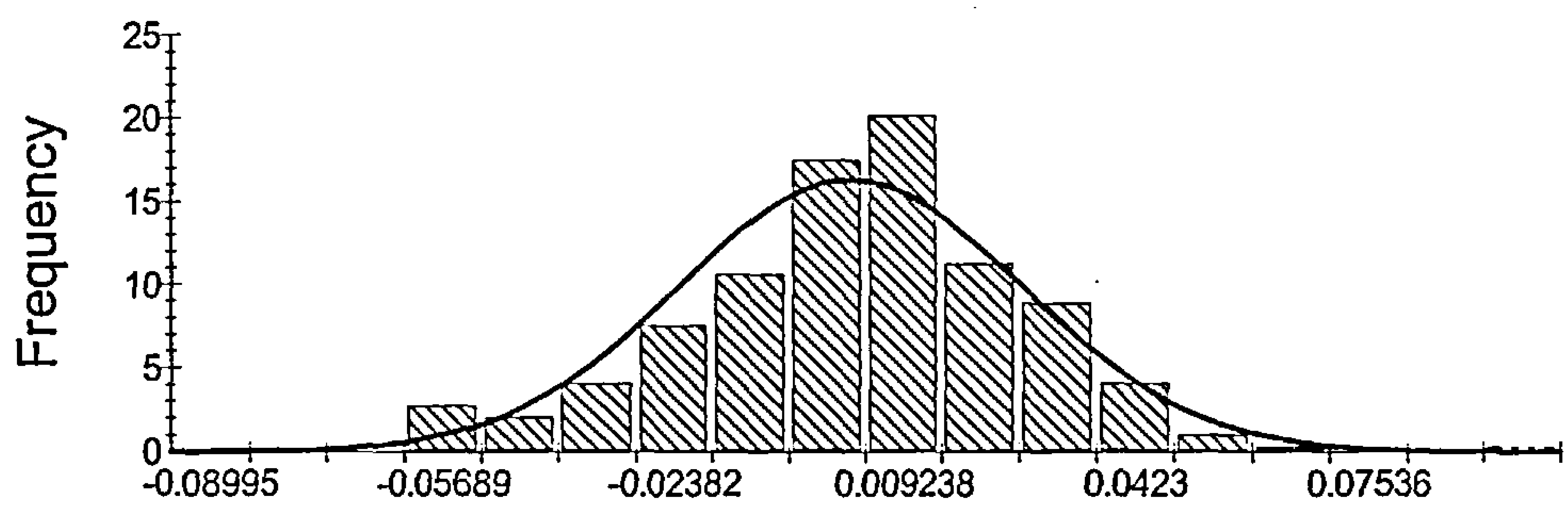


Table 3.4 shows the basic characteristics of the log returns of both indices.

Table 3.4: Distributional Statistics of Nifty and Midcap Daily Log Returns

	Nifty Index	Midcap Index
First Day in Sample	2 March 1999	2 March 1999
No. of Observations	265	265
Mean	0.0015	0.0026
Standard Deviation	0.0188	0.0244
Skewness	0.2953	-0.1412
Excess Kurtosis	1.6022	0.9580
Minimum	-0.0530	-0.0624
Maximum	0.0755	0.1029
Coeff. Of Variation	12.2066	9.3784
Correlation (r^2_t, r_{t-1})	-0.0246	-0.0202
Jarque-Bera Statistic	32.20 ***	11.01 ***
(99% $\chi^2(2)$ Critical Value)	(9.21)	(9.21)
0.01Percentile (of standardised returns)	-2.4841	-2.5912
0.2 Percentile	-0.7568	-0.7713
0.4 Percentile	-0.2418	-0.1314
0.6 Percentile	0.2294	0.2670
0.8 Percentile	0.6754	0.7952
0.99 Percentile	2.5741	2.0287
LM(1) ARCH test	4.9452 **	10.4349 ***
(95%, 99% $\chi^2(1)$ Critical Value)	(3.841, 6.635)	(3.841, 6.635)

Significance at the 99% and 95% level of confidence is denoted by *** and ** respectively.

The kurtosis of the distribution indicates whether the data are more peak-shaped or flatter than the normal distribution. The kurtosis is defined as:

$$\hat{K}_y = \frac{1}{n}\sum_{t=1}^{n}\frac{(r_t - \hat{\mu})^4}{\hat{\sigma}^4} \tag{3.5}$$

where n is the number of observations, r_t is the log return at time t, μ is the mean, and σ is the standard deviation. The kurtosis of a normal distribution is equal to 3, and a higher kurtosis value indicates a peak-shaped distribution. The excess kurtosis (kurtosis -3) values for the log returns of both indices are shown in Table 3.4, and confirm that the series are peak-shaped.

In addition, one may also look at the position of the central 0.2 percentile. These mid-20% observations in a normal distribution lie between the standardised values of +/- 0.251. The mid-20% (standardised) observations for the Nifty index lie between -0.242 and +0.229, whilst in case of the Midcap they lie between -0.131 and +0.267, indicating that the distributions are peak-shaped.

In inquiring whether the distributions of the index log returns are fat-tailed, one may compare the "extreme percentiles" of these distributions to those of the normal distribution. The 0.01 and 0.99 percentiles for the normal distribution occur at -/+ 2.326. As shown in Table 3.4, the 0.01 percentile occurs "earlier" than expected, indicating fat left tails for both indices. As regards the right tails, the position of the 0.99 percentile for the Nifty index indicates that the tail is fatter than normal, given that we enter this percentile "later" than expected. This does not occur in case of the Midcap index. Yet, the histogram of the latter index shown in Figure 3.5, indicates that the right tail becomes relatively fat at some point.

The asymmetry of the distribution is measured through the skewness defined as:

$$S\hat{K}_y = \frac{1}{n}\sum_{t=1}^{n}\frac{(r_t - \hat{\mu})^3}{\hat{\sigma}^3} \qquad (3.6)$$

where n is the number of observations, r_t is the log return at time t, μ is the mean, and σ is the standard deviation.

As shown in Table 3.4, the skewness of the Nifty log returns is positive, indicating a longer and/or fatter right side, whilst that of the Midcap log returns is negative, indicating a longer and/or fatter left side. Given this, one may state that NSE returns during the sample period were not considerably biased towards any one direction, although a more formal investigation would require analysing individual stock returns.

The final test of normality is the Jarque-Bera (1980) test. This test jointly considers the skewness and kurtosis of the distribution as follows:

$$JB_y = n\left[\frac{S\hat{K}_y^2}{3!} + \frac{(\hat{K}_y - 3)^2}{4!}\right] \xrightarrow{d} \chi_2^2 \tag{3.7}$$

where $S\hat{K}_y$ and $\hat{K}_y$ are the skewness and kurtosis of the distribution respectively. The test statistic is $\chi^2(2)$ distributed. As shown in Table 3.4, the Jarque-Bera statistic enables the rejection of the null hypothesis of a normal distribution at the 99% level of confidence, for both indices.

3.4.3 Heteroskedasticity of Logarithmic returns

The plots of logarithmic returns shown in Figures 3.2 and 3.3 indicate that it is plausible that both series feature a time-changing variance. A more formal yardstick which may be applied is the Lagrange Multiplier (LM) test statistic. The log returns are regressed on a constant, a lag and an error term as follows:

$$r_t = \beta_0 + \beta_1 r_{t-1} + u_t. \tag{3.8}$$

The LM statistic is then used to test whether there are autoregressive conditional heteroskedasticity (ARCH) effects in the error term u_t, (Engle, 1982). The squared residuals (u^2_t) are regressed on q squared residual lags:

$$\hat{u}^2_t = \alpha_0 + \rho_1\hat{u}^2_{t-1} + \rho_2\hat{u}^2_{t-2} + \ldots + \rho_q\hat{u}^2_{t-q}. \tag{3.9}$$

The null hypothesis of no ARCH effects ($\rho_1 = \rho_2 = \ldots = \rho_q = 0$) is tested against the alternative hypothesis that $\rho_1 \neq 0, \rho_2 \neq 0, \ldots \rho_q \neq 0$. The LM statistics for both indices are shown in Table 3.4 for ARCH(1) effects. These show that the null hypothesis of no ARCH effects can be rejected, at least at the 95% level of confidence. This is a typical feature of heteroskedastic time series where large returns tend to occur in clusters.

3.4.4 Symmetry of the Tails of the Logarithmic Distribution

In case of the NIFTY log returns, both the histogram as well as the 0.01 and 0.99 percentiles indicate asymmetry, in the sense that the right tail seems fatter than the left one. As for the Midcap index, the 0.01 and the 0.99 percentiles indicate asymmetry where the left tail is fatter than the right. Yet in this case, the right tail becomes fatter than the normal distribution at higher standardised values and the histogram seems to suggest a fatter right tail. Therefore, these indices do not confirm the observation of Franses and van Dijk (2000) that large negative returns occur more often than large positive returns. However, they are in line with the suggestions of Longin (1996) and Jondeau and Rockinger (2003), that asymmetry in the tails in any one particular direction is not a general characteristic of stock market returns.

3.4.5 High Volatility often follows Large Negative Returns

The methodology used by Franses and van Dijk (2000) to show that high volatility often follows large negative returns, was to work out the correlation between the squared return at day t and the return at day $t-1$.[24] A negative correlation coefficient indicates that the larger returns were likely to be preceded by a negative return. Table 3.4 reports negative correlation coefficients (r^2_t, r_{t-1}) for both indices, and this is in line with the observation of the above authors.

3.5 Concluding Comment

This chapter offered a background to the NSE and a preliminary analysis of the data set at hand. It is not claimed that all of the features evident in this sample are general characteristics of stock market data – indeed some may have been the result of a relatively short sampling period. Nonetheless, these features reveal that the sample does not deviate by much from the basic "stylized facts" of stock market data. Overall, there are numerous features which relate specifically to NSE. Some of these characteristics fall outside the sample period and therefore

[24] An alternative methodology for detecting the asymmetric response to volatility was outlined by Engle and Ng (1993). This methodology is adopted in Chapters 5 and 7.

do not affect the research results. Other features will be specifically analysed or accounted for in the empirical chapters where possible.

APPENDIX 3.1

Market Wide Circuit Breakers

The Market Wide Circuit Breakers system was introduced in July 2001. Trading halts in equity and derivatives markets are triggered by specified movements in the NSE Nifty or the BSE Sensex. Trading resumes after a period of time, which depends on the magnitude of the movement of the index, and whether the movement occurred in the morning or in the afternoon. When the fluctuation occurs in the afternoon, trading usually stops for the rest of the day. This happens to avoid resuming trading for a brief period given that the trading session usually stops at 15:30. Short trading sessions may not be desirable following large fluctuations. The NSE website specifies the following procedures in relation to circuit breakers:

- "In case of a 10% movement of either of these indices, there would be a one-hour market halt if the movement takes place before 1:00 p.m. In case the movement takes place at or after 1:00 p.m. but before 2:30 p.m. there would be trading halt for ½ hour. In case movement takes place at or after 2:30 p.m. there will be no trading halt at the 10% level and market shall continue trading".

- "In case of a 15% movement of either index, there shall be a two-hour halt if the movement takes place before 1 p.m. If the 15% trigger is reached on or after 1:00p.m. but before 2:00 p.m., there shall be a one-hour halt. If the 15% trigger is reached on or after 2:00 p.m. the trading shall halt for remainder of the day".

- "In case of a 20% movement of the index, trading shall be halted for the remainder of the day".

Source: www.nse-india.com ; accessed 3rd September 2003.

APPENDIX 3.2

Changes in Market Timings

During the initial part of the sample period, pre-opening and post-closing call auctions were held. Pre-opening call auctions were usually held between 09:30 and 09:45, followed by continuous trading till 15:30, and subsequently by a post-closing call auction between 15:30 and 15:45. Unexecuted orders from the continuous trading session were carried forward to the closing call auction. As from 9th June 1999, the initial and closing auctions were no longer held. Continuous trading was held between 10:00 and 15:30. The pre-opening and post-closing auctions were resumed on the 17th November 1999. The trading hours were as follows:

Pre-open Session: 09:45 to 09:55
Normal Market Open: 09:55
Normal Market Close: 15:30
Post-close Session: 15:35 to 15:50

Yet, during the above trading day, whilst the auction algorithm was working correctly, some display problems on the trading screen occurred, and the pre-open and post-closing auctions were suspended again, as from 18th November 1999.

The trading hours were amended as follows:
Normal Market Open: 10:00
Normal Market Close: 15:30

The market timings were revised again on 30th December 1999, as follows:
Normal Market Open: 09:00
Normal Market Close: 13:00

The above change was affected in connection with the preparation for any problems which might have arose due to the change in date at the start of the year 2000.

As from 3rd January 2000, the trading hours were:
Normal Market Open: 10:00
Normal Market Close: 15:30

As from 8th March till 17th March 2000, the market timings were:
Normal Market open: 09:55
Normal Market suspended from 11:00 till 11:30
Normal Market re-open: 11:35 after a pre-open of five minutes
Normal Market close: 16:00

The final revision in timings during the sample period occurred on 21st March 2000:
Normal Market Open: 09:55
Normal Market Close: 15:30

Information obtained from NSE Circulars: CMTR/01015, CMTR/01289, CMTR/01297, CMTR/01344, CC/01362, CMTR/01501, CMTR/01504 and CMTR/01531.

APPENDIX 3.3

Trading Holidays

02-Mar-99	Tuesday	Holi
29-Mar-99	Monday	Bakri-Id (Id-ul-zuha)
02-Apr-99	Friday	Good Friday
27-Apr-99	Tuesday	Moharrum
13-Sep-99	Monday	Ganesh Chaturthi
19-Oct-99	Tuesday	Dasara
07-Nov-99	Sunday	Diwali (Laxmi Puja)*
08-Nov-99	Monday	Diwali
23-Nov-99	Tuesday	Guru Nanak Jayanti
26-Jan-00	Wednesday	Republic Day
17-Mar-00	Thursday	Bakri-Id (Id-ul-zuha)
20-Mar-00	Monday	Holi

* *Muharat* trading was conducted during this holiday from 19:00 till 20:30. Yet, this trading day was deleted from the sample, given that the number of trades was less than 180,000, when a typical NSE trading day for the sample period featured around 400,000 trades.

CHAPTER 4:

AN ANALYSIS OF THE IMPACTS OF NON-SYNCHRONOUS TRADING ON PREDICTABILITY

4.1 Introduction

Theoretical models of market microstructure are often formulated in continuous time, yet empirical studies of securities markets use data sets which are necessarily in discrete time. This discrepancy may constitute a challenge to researchers aiming to investigate the validity of theoretical models by analysing empirical data. This challenge becomes more pronounced when the data include non-synchronous trading effects, meaning that some particular stocks do not trade for prolonged periods – yet researchers typically assume that the cross-section of prices was sampled simultaneously. Such assumptions may be vital for the sake of research manageability, yet they might also affect the validity of any inferences. For instance, the degree of efficiency on the market may be underestimated given that non-synchronous trading might give the impression that stock prices are not adjusting immediately to news.

For this reason, the market microstructure discipline stands to gain from a deeper understanding of non-synchronous trading effects as well as the increased availability of empirical evidence of these effects, gleaned through various methodologies. The main objective of this empirical study is to provide new evidence on this question. The strength of this analysis lies in three important respects: first, a new test method is proposed to identify the relation between predictability and non-synchronicity; second, it employs a high quality, high frequency dataset; and third, it uses data from an emerging stock market.

Most existing studies which tackled non-synchronous trading effects have focused on the autocorrelation structures of stock market data. In this chapter, I take a different approach, and focus on predictability and lead-lag effects in the values of two indices. Predictability effects are tested for using three different techniques; namely Pesaran-Timmermann tests, Vector Autoregressions and Granger-Causality, and Impulse Response Functions. The analysis then proposes a simple test in order to infer whether any predictability effects may be attributed to non-synchronous trading or whether they constitute actual delayed adjustments of traders' expectations.

A second important aspect of this empirical investigation lies in the use of high-frequency data, in addition to daily data – and the analysis breaks new ground in this respect. Following the notion that trading activity varies throughout the trading day, one may deduce that non-synchronous trading effects become more amplified during those periods when trading activity abates – usually towards the middle of the day. This implies that an intra-day data set is a prerequisite to obtain unbiased empirical evidence of non-synchronous trading effects.

A third noteworthy feature is the use of emerging market data in the context of non-synchronous trading. One may expect differences between the microstructure effects of stock market trading in emerging economies and those in the industrial economies, especially given the macro evidence on market differences. Emerging markets tend to exhibit higher serial correlation, less frequent trading and slower adjustment of prices to news (Bekaert and Harvey; 2002). The NSE provides an interesting setting for the analysis since it includes a significant proportion of less liquid securities. This enables the thorough investigation of the issues of efficiency and non-synchronous trading across stocks with different liquidity levels, using daily and higher frequency data.

The rest of the chapter is structured as follows: Section 4.2 reviews the existing literature whilst Section 4.3 describes the methodology and formulates the expected results for this study. Section 4.4 describes the data sets. Sections 4.5 - 4.7 test for predictability effects in the data set through different techniques. Section 4.8 investigates whether the observed predictability effects are more attributable to non-synchronous trading as opposed to actual delayed adjustments of expectations on part of traders. Section 4.9 concludes.

4.2 Research Background

Non-synchronous trading effects take place when different shares are traded at different intervals – in particular transactions in less liquid securities occur less frequently. In the latter cases, the last transaction price quotations might cease to reflect the fundamental value of the firm as new information becomes available. In this way, at each point in time, the cross-section of last trade prices reflects different overlapping information, some of which may be partly out-of-date. At face value, this gives the impression that the prices of some stocks delay in adjusting to new information; yet the underlying cause of the apparent inefficiency is that the most recent trading price relates to a past transaction, and the time since the last transaction varies across securities. Last transaction prices of infrequently traded securities might be used for calculating the value of a portfolio of stocks or the value of a market index. At times, the validity of this methodology is undermined since such calculations might be based on partly outdated data due to non-synchronous trading. The latter data does not imply that there still exist market participants who are willing to trade at those prices.

One problem with non-synchronous trading effects is that it is usually cumbersome for researchers to inquire the last transaction time for each and every stock and it is often assumed that securities prices were sampled simultaneously. Yet this might not necessarily be the case, say when working with a cross-section of security closing prices, and it might therefore amount to a limitation in the research methodology.

Non-synchronous trading induces particular characteristics in stock price data. For instance, stock price indices tend to exhibit higher levels of serial correlation than individual stocks, as discussed by Fisher (1966). Cohen, Maier, Schwartz and Whitcomb (1979) showed that non-synchronous trading induces serial correlations in market returns. Clare, Smith and Thomas (1997) in an analysis of UK stock data, found that smaller stocks feature higher levels of serial correlation, which they attributed to thin trading.

Atchison, Butler and Simonds (1987) compared the serial correlation of a portfolio of NYSE stocks to that predicted by a model of non-synchronous trading as proposed by Scholes and Williams (1977). They found that the actual serial correlation was higher than that predicted by the non-synchronous trading model, and they attributed this to other sources of delayed price adjustment. There might be various reasons why prices take longer to adjust to new information. For instance, as discussed in Chapter 2, market participants who submit limit orders do not necessarily monitor these orders continuously. As new information becomes available, such orders may become mispriced and other participants might "pick off" these orders to trade profitably. In this way a transaction which occurs at an outdated price might still be consistent with market efficiency, since an efficient market does not require *all* market participants to adjust expectations instantaneously. A further reason why a delayed price adjustment may occur is that participants might not devote enough time in monitoring less liquid stocks, as they do with the most liquid ones. Thus, new information relating specifically to the former stocks might take longer to get priced in. Therefore, not all of the pricing delays which are evident in stock price data are the result of non-synchronous trading. A related idea as discussed by Jegadeesh and Titman (1995) is that the serial correlation of returns is the result of stock price over-reactions rather than actual lead-lag relationships. In particular, stock prices tend to overreact to company-specific news, but there tends to be a delayed reaction to general economic news.

Clare, Morgan and Thomas (2002) used monthly data for shares trading on the London Stock Exchange in order to gauge the serial correlation characteristics of those stocks which are less prone to non-trading periods. The use of monthly data enabled the authors to adopt an innovative approach based on the notion that shares trading at the close of the sampling interval (i.e. the last day of the month) do not suffer from non-trading. In this way, the authors created a control portfolio, comprising stocks which trade at the end of the month which should be less prone to non-synchronicity. The authors reported positive serial correlation across size-sorted portfolios, which becomes more pronounced in the case of those portfolios comprising smaller stocks. One key result of the study is that the control portfolio still features significant serial correlation, and therefore this feature may not be exclusively attributed to the non-trading of stocks. One possible source which may account for the correlation which may not be attributed to non-trading is the presence of "positive feedback traders" who buy/sell stocks as prices rise/fall.

Various authors have investigated the effects of non-synchronous trading on the autocorrelation of stock returns, and these include Lo and MacKinlay (1990), Boudoukh, Richardson and Whitelaw (1994) and Kadlec and Patterson (1999). All these studies conclude that non-synchronous trading increases return serial correlation, but they disagree as to what is the specific autocorrelation level which emanates from non-synchronous trading. Part of the discrepancy in between the studies may be attributed to the differing assumptions as regards the non-trading intervals of securities.

An "explicit" case of non-synchronous trading was analysed by Papachristou (1999) in the context of the Athens Stock Exchange. Prior to 1989 the trading day on this exchange consisted of successive trading sessions, and shares of a particular industry traded in each of the sessions. Thus, the returns reported at the end of the day – and therefore the closing index value – constituted partly "outdated" information since they related to transactions which took place earlier on during the day. The non-trading periods for the particular stocks in this case were deterministic, and the author called this "deterministic non-synchronicity". The author showed that the overall effects are similar to those of stochastic non-synchronicity, including serial correlation in market index returns and cross-correlation in between stocks.

A further possible source of serial correlation in returns on some exchanges is the existence of price limits (Chang, McLeavey and Rhee; 1995). When the prices of particular stocks are adjusting to news, prices might hit the limit, and thus the required adjustment would have to resume at a later stage. Now, according to the empirical evidence of Kim and Limpaphayom (2000) in the context of Asian markets, *active* stocks and *small* stocks tend to hit price limits more frequently. In the context of India, NSE adopted a system of price limits ranging from 8% to 50%, as outlined in Chapter 3. For price limits to result in frequent lead-lag effects from larger to smaller capitalisation stocks, it would be required that smaller stocks hit price limits more frequently than larger capitalisation ones. Yet, this does not seem to be the case, since intuitively *both* the larger and the smaller stocks are more prone to hit price limits. Smaller stocks are more prone to hit price limits (Kim and Limpaphayom; 2000), whilst given that larger NSE stocks trade more actively (Tables 4.3 and 4.4) the latter stocks are more prone to hit price limits as well, as per the evidence of the former authors. Thus, we may not speak of any possible lead-lag effects as between stocks with varying liquidity characteristics, due to price limits.

Furthermore, given that this investigation uses index data computed through a cross-section of fifty stocks, the effect of one single stock occasionally hitting a price limit is not likely to lead to material restraints on the indices from reflecting the fundamental value. This argument is not applicable to non-synchronous trading effects. Whereas one may only expect a handful of stocks in an index to hit price limits on a particular day, non-synchronous trading effects should transpire in a larger number of stocks in the smaller-capitalisation index. This is due to the fact that smaller stocks trade less frequently as compared to the larger ones (Tables 4.3 and 4.4).

Overall, the presence of price limits does not affect the main notion of this analysis (in that the main research question is whether any lead-lag effects are resulting from actual delays in traders' adjustments to news as opposed to market microstructure effects). Such microstructure effects are likely to constitute non-synchronous trading rather than price limits, given that price limits are not expected to lead to causality in any given direction. In addition, whilst any presence of non-synchronous trading is likely to affect a high proportion of less traded stocks, it should be unlikely that a similar proportion of stocks comprising the index hit the price limit simultaneously. Furthermore, whilst non-synchronous trading effects tend to recur throughout the year on those stocks which suffer from this factor (since lower trading activity would be typical in such stocks throughout most trading days), securities tend to hit price limits only on a handful of days.[25] In this way, any market microstructure effects observed in this analysis are more likely to constitute non-synchronous trading rather than stocks hitting price limits.

Despite this, one cannot discard the possibility that any lead-lag effects which are not related to delayed traders' adjustments are due to price limit restrictions rather than to non-synchronous trading. Both phenomena imply less frequent transactions – non-synchronous trading is related to temporary absence of transactions, whilst price limits are likely to result in lower trading activity given that trading in the particular stock may be suspended upon hitting the price limit. In addition traders may take the view that prices close to the limit are "fake" and they may be reluctant to trade at such prices.

Given that changes in expectations may take longer to show up in share price fluctuations if the latter trade infrequently, non-synchronous trading may result in lead-lag effects in between the prices of various stocks. This induces predictability in the data. Yet, this degree of predictability does not necessarily translate into abnormally profitable trading opportunities, as shown by Day and Wang (2002) after simulating a trading strategy in the Dow Jones Industrial Average index which was adjusted for non-synchronous trading effects.

The aim of this study is to investigate the lead-lag effects as between two indices which differ in their degree of non-synchronous trading. Intuitively, one may expect that the index which features the less liquid securities will "take longer to adjust to new information" and therefore the more liquid index will lead the less liquid one. This is one of the first studies that analyse lead-lag relationships between two indices, in the context of non-synchronous trading effects as the central issue. Previous non-synchronous trading studies tended to focus on the serial correlation structure of the return data. Conversely, most studies of lead-lag relationships as between indices or stock portfolios do not place their principal emphasis on non-synchronous trading. However, some of the findings of the latter studies are relevant to non-synchronous trading, for example Lo and MacKinlay (1990) and Conrad, Gultekin and Kaul (1991).

Lo and MacKinlay (1990) analysed US stock price data which were sampled at different inter-day frequencies. They found that large-capitalization stocks tend to lead the stocks of smaller companies. One important factor which results in such "causality" is the cross-correlation

[25] No statistics regarding the frequency of price limit hits on NSE were available, but relying on similar statistics reported by Kim and Limpaphayom (2000) for the period 1990-1993, stocks on average hit price limits on 27 trading days on the Taiwan Stock Exchange, whilst they hit price limits on 8 trading days on the Thailand Stock Exchange.

between stocks over time. The latter may be a by-product of non-synchronous trading, as shown by various authors such as Cohen, Maier, Schwartz and Whitcomb (1979). Conrad, Gultekin and Kaul (1991) used GARCH methodology to study the transmission of volatility between different size-sorted portfolios comprising various US stocks, sampled at weekly intervals. The authors found that volatility in larger stocks affects the volatility of smaller stocks, but the reverse does not apply. The authors noted that one possible cause of these dynamics is that general economic news might first be impounded in the larger-capitalisation stocks, and subsequently in smaller stocks. The related findings of Chan and Hameed (2006) in the context of various emerging markets, indicate that stocks which attract more attention on part of analysts lead those stocks which are analysed less closely, even after controlling for firm size.

The only papers which directly addressed lead-lag effects in the context of non-synchronous trading are Chiao, Hung and Lee (2004) and Poshakwale and Theobald (2004). Chiao, Hung and Lee (2004) reported a contemporaneous relationship between Taiwanese stocks of different market capitalisation, implying that smaller stocks do not take longer to adjust than larger ones. Yet, the latter study used weekly and monthly data; whereas non-synchronous trading should be essentially a shorter-term phenomenon. In particular, with the typical surge in trading activity at the end of the trading day, it might be the case that the smaller stocks "make up" for the delayed adjustments during the day, and thus no non-synchronous trading effects would be detected using daily data frequency. Thus, one may expect that the analysis of non-synchronous trading effects using high frequency data should be an important supplement to the existing literature.

Like the present study, Poshakwale and Theobald (2004) employed Indian data from the National Stock Exchange and the Bombay Stock Exchange.[26] The authors used daily data frequency, and in contrast to Chiao, Hung and Lee (2004), they found traces of lead-lag effects in the data from larger to smaller stocks, even after adjusting for thin trading effects in the smaller stocks. The authors found that roughly 50% of the predictability derives from non-synchronous trading, whilst the rest is attributable to a mixture of non-synchronous trading and different speeds of adjustment. Whilst the paper by Poshakwale and Theobald (2004) is similar to this investigation, there is still an added value in the latter analysis. In particular, this analysis employs higher frequency data which offer higher potential for

[26] This paper was published after finishing the preliminary draft of this investigation.

gleaning evidence of non-synchronous trading effects, and in addition, there is still a possibility of obtaining contrasting results.

This analysis seems to be the first one that tests for lead-lag relationships between two indices, using high-frequency data with the specific aim of gleaning evidence of non-synchronous trading effects. Using a high-frequency data set is important given that intra-day factors might be more relevant to analysing such effects from a market microstructure point of view as discussed in Section 4.3.5.

4.3 Methodology and Expected Results

This analysis applies various methodologies to investigate the effects of non-synchronous trading on data predictability, in terms of lead-lag effects. These methodologies constitute Pesaran-Timmermann tests, Granger Causality and Vector Autoregressions (VARs), and Impulse Response Functions (IRFs), as described in Sections 4.3.1, 4.3.2 and 4.3.3. The methodology which is used to infer whether the observed predictability emanates from non-synchronous trading or market inefficiency is to investigate the returns during and following trading breaks, as discussed in Section 4.3.4. The subsequent section considers result expectations.

4.3.1 Pesaran-Timmermann Tests

The test proposed by Pesaran and Timmermann (1992) measures the dependence between two time series, in terms of whether they fluctuate in the same direction. Therefore, this non-parametric test considers the direction of the changes and ignores the magnitude of the fluctuations. The procedure tests the null hypothesis that the series are independent, and the test statistic is normally distributed in case of large samples.

The test statistic for assessing the relationship between variables x_t and y_t is computed as follows:

$$S_n = \frac{\hat{P} - \hat{P}_*}{\sqrt{\{\hat{V}(\hat{P}) - \hat{V}(\hat{P}_*)\}}} \xrightarrow{a} N(0,1) \tag{4.1}$$

where

$$\hat{P} = \frac{1}{n}\sum_{t=1}^{n} Sign(y_t x_t) \tag{4.2}$$

$$\hat{P}_y = \frac{1}{n}\sum_{t=1}^{n} Sign(y_t) \tag{4.3}$$

$$\hat{P}_x = \frac{1}{n}\sum_{t=1}^{n} Sign(x_t) \tag{4.4}$$

$$\hat{P}_* = \hat{P}_y\hat{P}_x + (1-\hat{P}_y)(1-\hat{P}_x) \tag{4.5}$$

$$\hat{V}(\hat{P}) = \frac{1}{n}\hat{P}_*(1-\hat{P}_*) \tag{4.6}$$

$$\hat{V}(\hat{P}_*) = \left[\frac{1}{n}(2\hat{P}_y - 1)^2\hat{P}_x(1-\hat{P}_x)\right] + \left[\frac{1}{n}(2\hat{P}_x - 1)^2\hat{P}_y(1-\hat{P}_y)\right] + \left[\frac{4}{n^2}\hat{P}_y\hat{P}_x(1-\hat{P}_y)(1-\hat{P}_x)\right] \tag{4.7}$$

and the function *Sign(Z)* takes a value of 1 when the variable is positive and zero otherwise.

Thus, $\hat{P}$ is a measurement of the number of occurrences where both time series changed in the same direction – it takes a maximum value of 1 when all the respective changes are in the same direction, and a minimum value of 0 when all contemporaneous changes are always in an opposite direction. The terms $\hat{P}_*$, $\hat{V}(\hat{P})$, and $\hat{V}(\hat{P}_*)$ adjust this "crude" measurement by considering the individual proportions of negative and positive changes in both of the series, and scale the original measurement to a normal distribution.

Pesaran-Timmermann tests may be used to detect lead-lag effects when applied to the relationships between x_t and y_{t-n} or between x_{t-n} and y_t.

4.3.2 Vector Autoregression and Granger-Causality

Vector Autoregression (VAR) methodology is based on the principle of Granger-Causality. Granger (1969) argued that if shocks in a particular time series lead to shocks in another time series, then the former series is "Granger-causing" the latter. In this way, VARs model a time series as an AR process, with the added lagged terms of another time series and an error term. If the lags of the second time series are significant, then one may argue that the latter is Granger-Causing the dependent variable. Thus, VARs offer the potential for modelling causal and feedback effects, where two or more time series Granger-cause each other.

The term "Granger-Causality" does not imply actual causality. For instance, it might be the case that the inter-relationships between the time series might be caused by an exogenous variable. Therefore, Granger-Causality modelling should be accompanied by an underlying theoretical relationship since otherwise the model may be incorrectly specified.

A bivariate VAR may be formulated as follows:

$$x_t = \sum_{i=1}^{n} \alpha_{1i} x_{t-i} + \sum_{i=1}^{n} \beta_{1i} y_{t-i} + u_{1t} \tag{4.8}$$

$$y_t = \sum_{i=1}^{n} \alpha_{2i} x_{t-i} + \sum_{i=1}^{n} \beta_{2i} y_{t-i} + u_{2t} \tag{4.9}$$

where x_t and y_t are the variables that are assumed to Granger-cause each other, whilst u_t is an error term.

This can be written in vector-matrix notation:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} \alpha_{1i} & \beta_{1i} \\ \alpha_{2i} & \beta_{2i} \end{bmatrix} \begin{bmatrix} x_{t-i} \\ y_{t-i} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \tag{4.10}$$

Granger-Causality methodology has been used to analyse relationships between stock prices and a variety of other variables. For instance, the relationship between fundamentals (such as the dividend growth rate) and stock prices was tested by Mavrides (2000), the relationship between stock prices and trading volume was analysed by Hiemstra and Jones (1994) and Silvapulle and Choi (1999), the interdependence of asset markets in different countries was analysed by Östermark (1998) and Hamori and Imamura (2000), and the relationship between stock prices and exchange rates was analysed by Granger, Huang and Yang (2000).

One persistent argument concerning Granger-Causality is whether the latter implies market inefficiencies, in the sense that if an index fluctuation leads to a fluctuation in another index, this would mean that if the first fluctuation was justified on the grounds of new information, the latter fluctuation should have occurred at the same time, ruling out lead-lag effects. Various authors such as Niarchos and Alexakis (1998) argue that Granger-Causality from one price series to the other may be taken as evidence against market efficiency.

Therefore when testing for Granger-Causality using daily data, one should expect contemporaneous (but not lagged) relationships if the markets are efficient and if there are no non-synchronous trading effects. This research also uses high frequency data sampled at one minute intervals. In the latter case, one may reasonably expect some lagged relationships. For instance prices of the most liquid stocks adjust instantly to news, whilst in case of less liquid stocks one may expect that the adjustment occurs later. The latter effect might not necessarily imply that traders are inefficient. Following non-synchronous trading arguments, it might be the case that the security does not trade immediately after the news; in this way the prices which are used for the purpose of calculating index values might be "outdated ones", giving the impression that the traders did not adjust their view about the value of the security. Thus when considering high frequency data, one may expect not to reject the existence of Granger-Causality.

VAR and Granger-Causality are subject to a number of limitations as outlined underneath. Firstly, Granger-Causality does not imply actual causality. In the current context, the indices may be influenced by an exogenous variable, and therefore the actual causality might run from the extraneous variable to the time series being studied. This argument may be relevant to the Indian stock markets, when considering the empirical evidence presented by Lamba (2003) that Indian equities are influenced by the markets of developed countries such as US, UK and Japan. Capelle-Blancard and Raymond (2002) show that cross-country linkages may emanate both from market-wide information and non-fundamental factors such as herding and traders adopting similar trading rules. In the context of this analysis, the "shortcoming" that Granger-Causality might not constitute actual causality is implied throughout the chapter, since it is confirmed that the observed predictability is largely the result of non-synchronous trading effects rather than actual causality.

The inferences obtained by the Granger-Causality model may be affected by the sampling process (Renault, Sekkat and Szafarz, 1998). This tends to happen when researchers analyse discrete price series, when the underlying theoretical model assumes continuous time. In addition, linear Granger-Causality tests may fail to detect non-linear causal relations as discussed by Baek and Brock (1992) and Hiemstra and Jones (1994). Non-linearity implies that the extent of the dependency between the time series varies during the sample period.

Engle and Granger (1987) argued that VAR estimates obtained when analysing differenced data of cointegrated time series may be flawed, since that the VAR excludes the error correction terms which appear in cointegration models.[27]

4.3.3 Impulse Response Functions

VAR models may be used to generate Impulse Response Functions (IRFs) as shown for instance by Sims (1980). IRFs trace the response of each of the variables in the system, to a shock in a given variable. Usually, a shock to the variable x_t has the largest effect on subsequent realisations of that variable itself. Yet if the VAR model predicts that the variable x_t is affecting other variables in the system, the latter should respond to the initial shock in x_t – usually the latter responses are lower than the subsequent fluctuations in x_t due to the shock.

The IRF of variable y_t to a shock in variable x_t which occurs at time t, may be viewed as the difference between two time series:

- The realisations of the time series y_t after the shock in x_t has occurred; and
- The realisations of the time series y_t which would have been observed in the absence of the shock in x_t, during the same time period.

The above may be formulated as follows:

[27] Cointegration tests that were performed on the data sets used in this analysis showed that the series were not cointegrated, and therefore this limitation is not relevant to this analysis.

$$IRFy(n,\delta,\omega_{t-1}) = E[y_{t+n}|\varepsilon_t = \delta, \varepsilon_{t+1} = ... = \varepsilon_{t+n} = 0, \omega_{t-1}] \\ - E[y_{t+n}|\varepsilon_t = 0, \varepsilon_{t+1} = ... = \varepsilon_{t+n} = 0, \omega_{t-1}] \quad (4.11)$$

where y is the time series of interest, δ is the shock taking place at time t, ω_{t-1} is the history of the time series, ε denotes an innovation, and the IRF is generated from time t to $t+n$. As shown in the equation, the intermediate innovations are assumed to be equal to zero, and this may be considered as a limitation of orthogonalised versions of IRFs. Another weakness of orthogonalised IRFs is that the actual results may vary, depending on the order in which the variables are specified in the VAR model.

In order to overcome the above limitations, Koop, Pesaran and Potter (1996) introduced the Generalised Impulse Response Function (GIRF), where the expectations of y_{t+n} are only conditional on the shock and the history of the series. This can be written as follows:

$$GIRFy(n,\delta,\omega_{t-1}) = E[y_{t+n}|\varepsilon_t = \delta, \omega_{t-1}] - E[y_{t+n}|\omega_{t-1}] \quad (4.12)$$

4.3.4 Trading Break Returns

The analysis of trading break and post-trading break returns is relevant for inferring whether delayed price adjustments in the data, mainly emanate from traders' delays in updating their expectations or whether they are more attributable to non-synchronous trading. Here, the term "trading break" refers to the ceasing of trading activity at the end of the day till the subsequent morning (and at times till after the weekend). It is assumed that during a trading break, market participants have enough time to adjust their judgements regarding the fundamental value of the firms, and that any outdated limit orders are cancelled. This appears to be a reasonable assumption for overnight and weekend breaks.

Given this, one may assume that any trades which occur immediately after a trading break will reflect the underlying market value of the particular firms and one may rule out any delayed price adjustments on part of the traders. This implies that if lead-lag effects as between the indices persist immediately after the trading break, they must be mainly due to non-synchronous trading effects rather than mispriced trades. Non-synchronous trading effects can still coexist with trading breaks given that an infrequently traded stock, might still take longer to trade immediately following the trading break. This results in a delayed adjustment of market price data – yet it is reasonable to assume that traders' expectations would have already been adjusted by the time that trading was resumed. This test is discussed further in Section 4.8, in the context of the empirical setting.

4.3.5 Formulating the Expected Results for this Study

The novel approach in this study is that the effects of non-synchronous trading are investigated in terms of leads and lags between two market indices which feature differing degrees of liquidity. The more liquid index may be expected to lead the less liquid one. Any lead-lag effects might be consistent with market participants taking longer to adjust their judgement regarding the fundamental value of the firms which trade less frequently. Yet, such lead-lag effects may simply be the result of non-synchronous trading effects in the data. In line with prior literature, one may expect both of the former factors to be contributing to lead-lag effects.

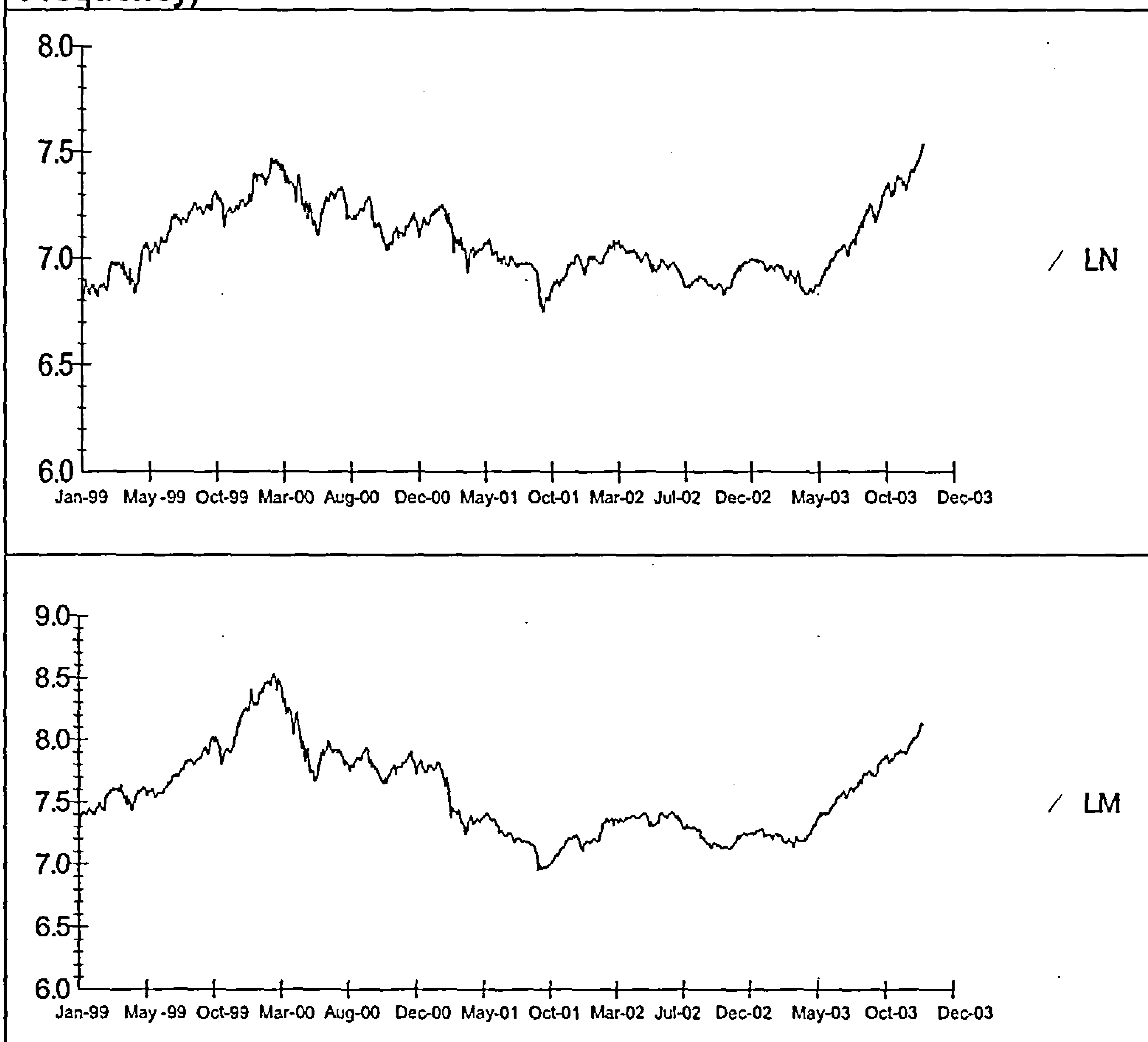
Another novel contribution in this analysis emanates from the use of a high-frequency data set, in addition to a daily data set. One may expect non-synchronous trading effects to be more prominent in a high-frequency data set and this rests on the fact that trading activity typically varies throughout the trading day. Non-trading periods for less liquid stocks might be more likely to occur during particular periods of the day, and such effects require a high-frequency data set to detect. Empirical studies point at a rise in trading activity at the end of the day. In our empirical setting of NSE, trading activity peaks at the end of the day, as discussed by Shah and Sivakumar (2000). This implies that non-synchronous trading effects become less significant at the end of the day, and thus more difficult to detect when using a data set which is based on closing prices.

Summing up, the main expectations are that the more liquid index leads the less liquid one and that such an effect becomes more pronounced when analysing the high frequency data set. Based on the inferences of previous studies, such predictability elements should be partly attributable to actual delays in price adjustments as well as due to non-synchronous trading. At the end of the Chapter, I investigate which of the latter causes is more relevant in explaining the observed lead-lag effects.

4.4 Data Set Characteristics

The daily data consist of the closing observations of the NSE Nifty and Midcap indices – the main index and the smaller capitalisation index respectively. Each index comprises 50 stocks and no security may be included in both indices. The reader is referred to Chapter 3 for a more detailed background of the main indices and NSE setup. The daily data period ranges from 1st January 1999 to 31st December 2003 – a total of 1257 observations.

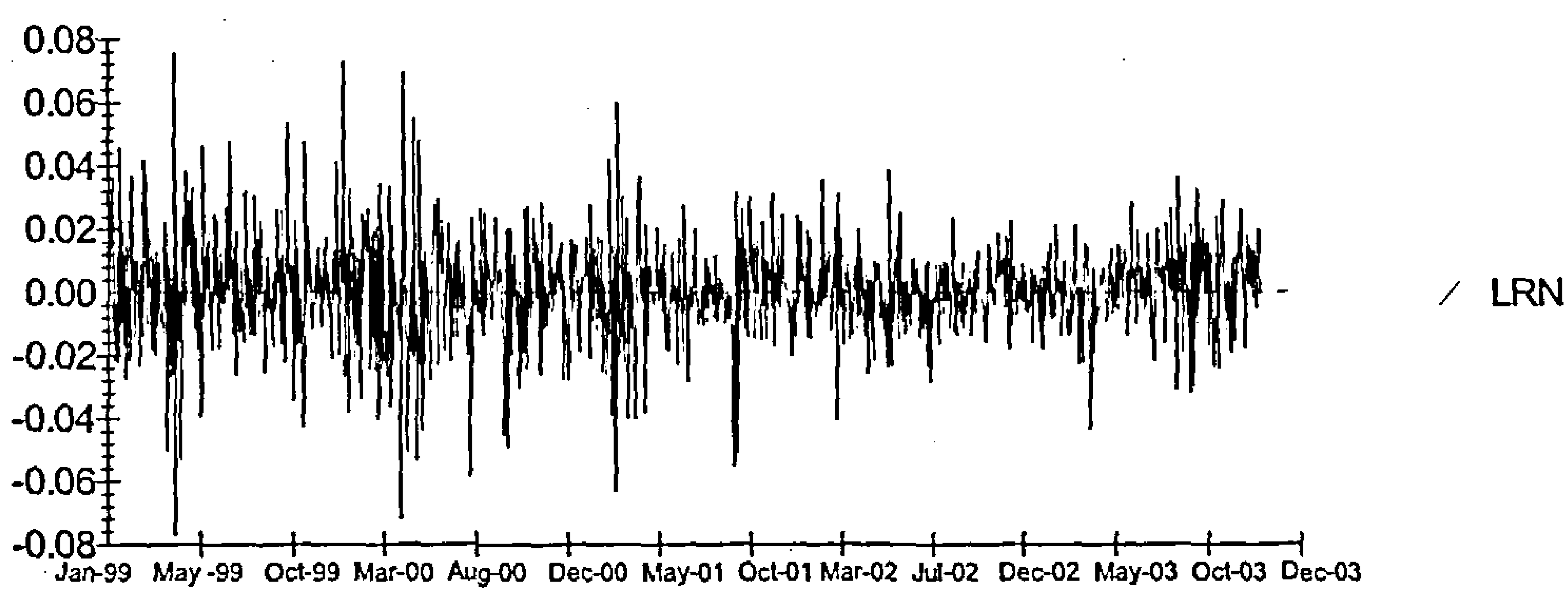
Figure 4.1: Logarithmic Series for Nifty (LN) and Midcap (LM) (Daily Frequency)

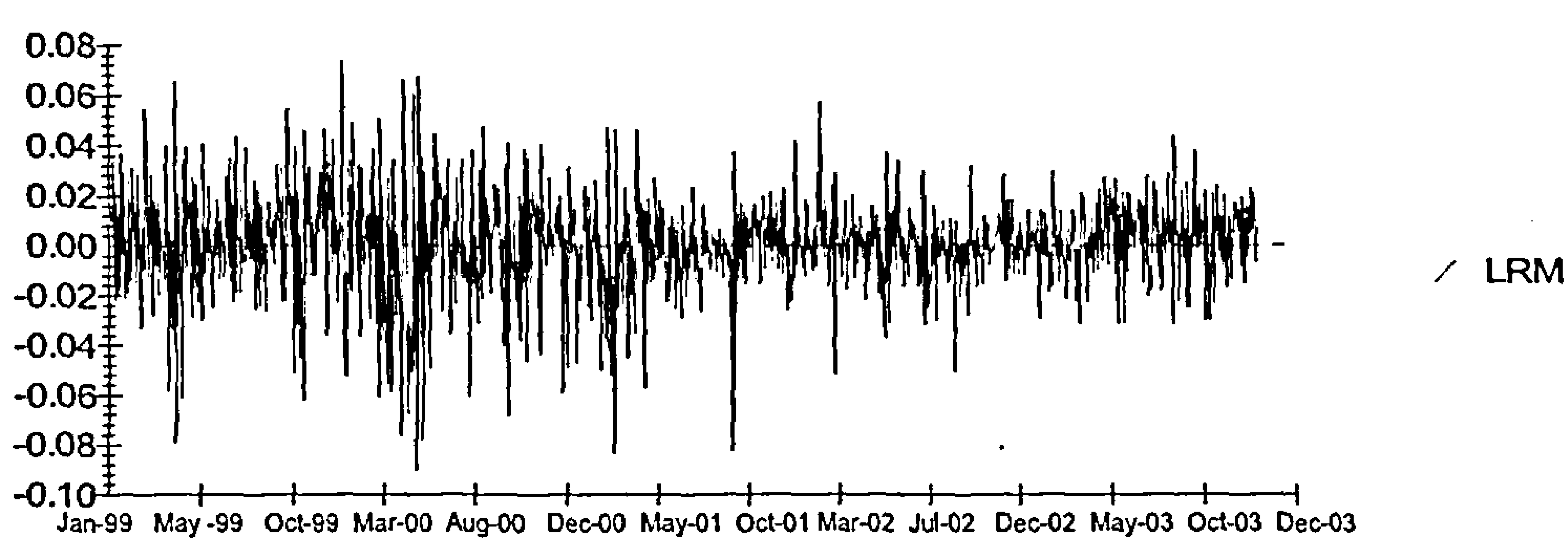


The high frequency data set consists of the values of both indices, sampled at one minute intervals, over the period ranging from 15th June 1999 to 25th June 1999. This period includes nine continuous trading sessions starting at 10 a.m. and ending at 3.30 p.m., yielding a total of 2970 observations.

Each high frequency data file showed tick-by-tick changes in the value of the Nifty and Midcap indices. In some instances there were seven (different) observations for each second, totalling to approximately 420 observations for the particular minute. In sampling the data, the first observation for the particular minute was taken. The observations typically started at 10:00 and ended at 15:29 yielding a total of 330 one-minute observations for each trading day.

Figure 4.2: Log Return Series for Nifty (LRN) and Midcap (LRM) (Daily Frequency)





Figures 4.1 and 4.2 show the logarithmic series and log return plots for both indices, sampled at daily intervals. Figures 4.3 and 4.4 show logarithmic series and log return plots for both indices, sampled at one minute intervals. Summary statistics and ADF tests of different orders are shown in Table 4.1 (daily data) and Table 4.2 (intra-day data).

Both in the case of the daily and one minute frequency data sets, the Augmented Dickey Fuller tests do not reject the null hypothesis of a unit root when considering the logs of the series. The null hypothesis of a unit root is rejected when considering the logarithmic returns.

This implies that the logarithmic prices may be classified as I(1) since they are stationary in the first differences.

Table 4.1: Daily Interval Data Set

Properties of Nifty and Midcap Logarithmic Series (LN and LM) and Nifty and Midcap Log Returns (LRN and LRM)

Variable	LN	LM	LRN	LRM
Maximum Value	7.539	8.534	0.075	0.074
Minimum Value	6.750	6.953	-0.077	-0.090
Mean	7.083	7.565	0.001	0.001
Std. Deviation	0.167	0.345	0.016	0.020
Skewness	0.438	0.584	-0.174	-0.547
Excess Kurtosis	-0.743	-0.321	2.614	1.972
Jarque-Bera Test [(a)]	69.2 ***	76.9 ***	363.8 ***	266.1 ***
ADF Test Statistics (Excluding Trend) [(b)]:				
ADF (1)	-1.11	-0.71	-25.12	-23.59
ADF (5)	-1.18	-0.76	-14.15	-13.68
ADF (10)	-1.30	-1.07	-10.15	-8.75
95% Critical Value	*-2.86*	*-2.86*	*-2.86*	*-2.86*
ADF Test Statistics (Including Trend) [(b)]:				
ADF (1)	-1.00	-0.40	-25.13	-23.60
ADF (5)	-1.08	-0.47	-14.16	-13.71
ADF (10)	-1.20	-0.86	-10.17	-8.79
95% Critical Value	*-3.42*	*-3.42*	*-3.42*	*-3.42*

The above statistics are based on a time series of 1257 (price level) observations. Statistical significance at the 99%, 95% and 90% level of confidence is denoted by ***, ** and * respectively.

(a) The Jarque-Bera test for normality, is $\chi^2(2)$ distributed. The critical values are 9.21, 5.99 and 4.61, for the 99%, 95% and 90% confidence levels respectively, rejecting the null hypothesis of a normal distribution.

(b) The Augmented Dickey-Fuller statistics, test the null hypothesis of a unit root. The ADF(n) statistic is the t-ratio of ρ in the model

$\Delta X_t = \alpha + \rho\delta t - \rho X_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta X_{t-i} + \varepsilon_t$, t=1,...,z. The 95% critical values of the test are shown in MacKinnon (1991). The ADF tests do not reject the null hypothesis of a unit root for the logarithmic series. The null hypothesis of a unit root is rejected when considering the logarithmic returns.

An informal procedure which may be used to cross-check this test is to look at the autocorrelation of the series at different lags. High autocorrelation coefficients which decline slowly may be taken as an indication of a unit root. The autocorrelation coefficients shown in Appendix 4.1 indicate that the logarithmic series are I(1).

Figure 4.3: Logarithmic Series for Nifty (LN) and Midcap (LM) (One Minute Frequency)

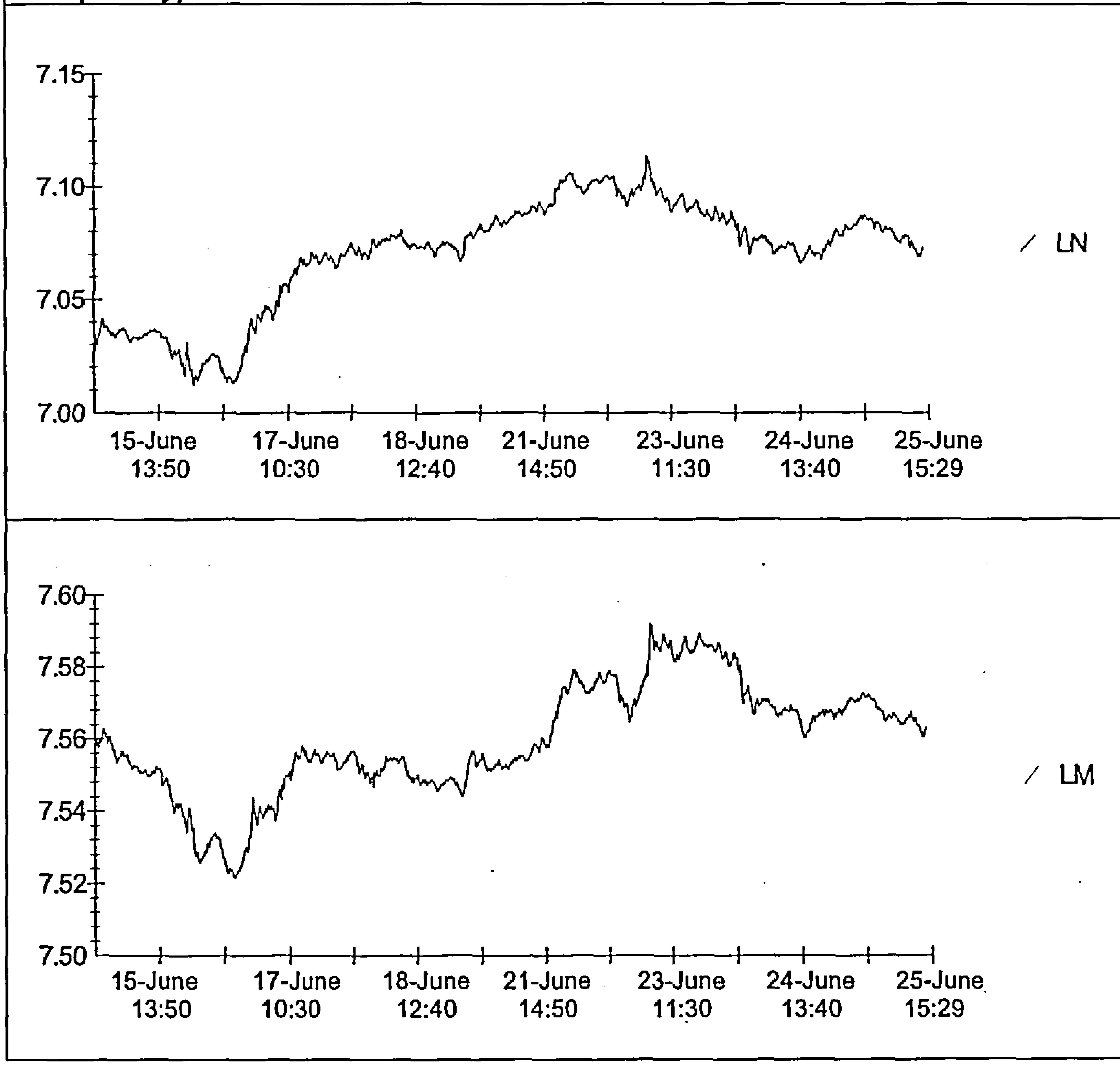
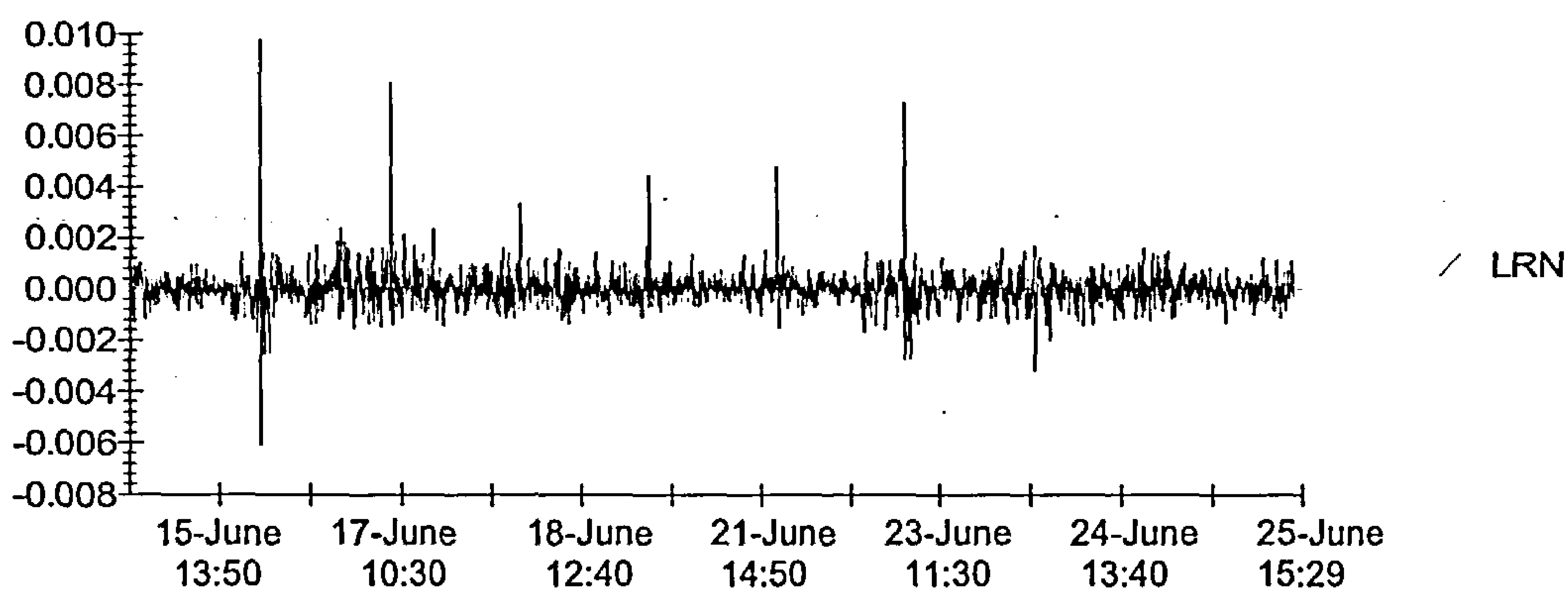
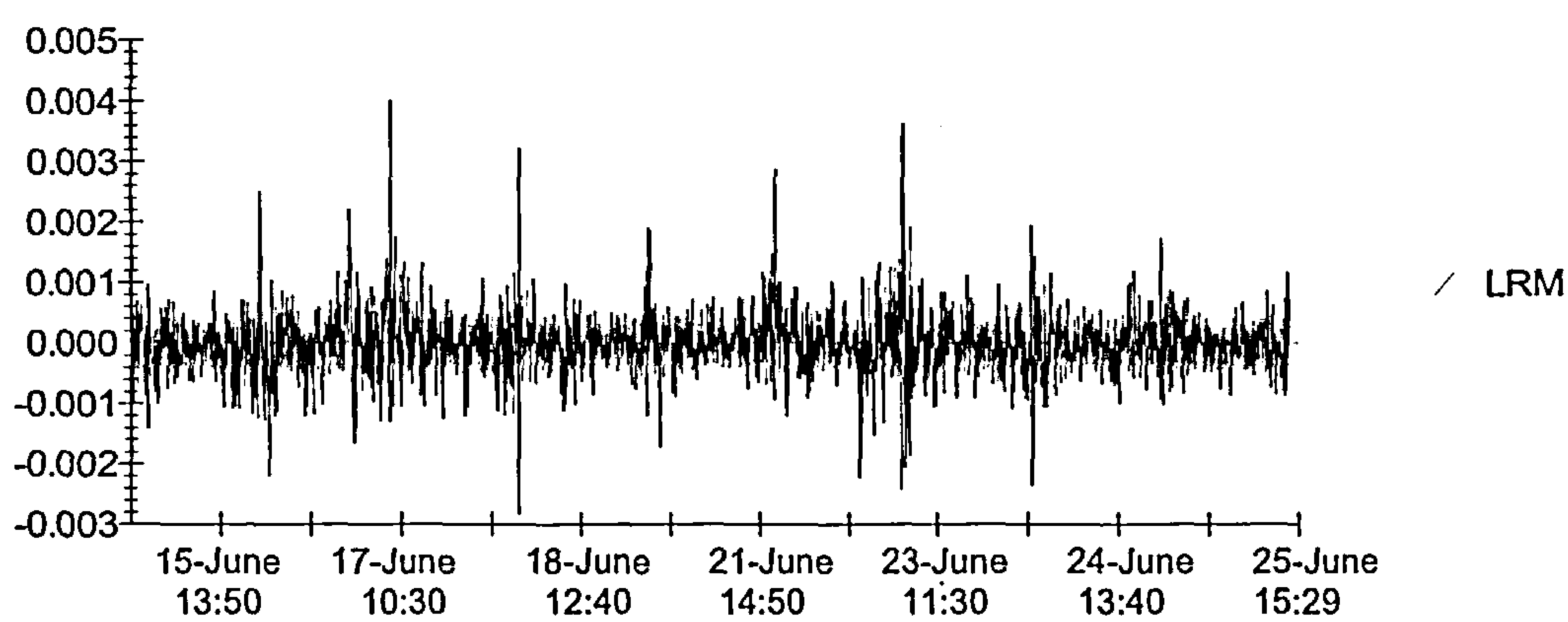


Figure 4.4: Log Return Series for Nifty (LRN) and Midcap (LRM) (One Minute Frequency)





Given that non-synchronous trading effects depend on the level of liquidity, it is important to assess the relative liquidity of the respective indices. One may expect the main index (Nifty) to be more liquid than the smaller capitalisation index (Midcap), since larger capitalisation companies are likely to be more popular amongst traders. Yet, an empirical investigation about the trading frequencies of the shares included in the indices was undertaken to confirm this notion.

Table 4.3 shows the average trading frequencies for the individual shares in the Nifty and the Midcap index. Given that the individual shares in the indices change periodically, the index composition as at the time of writing (18^{th} May 2003) was chosen, largely due to the unavailability of index composition historical data. The sampled trading days are included in both the daily and the high frequency data sets, and this restricted the potential sample to 9 trading days (since the latter data set consists of 9 trading days). Alternate trading days from the high-frequency data set were chosen. Given this, such preliminary investigation suffers from various limitations. In particular, it is assumed that the index compositions and the respective liquidity levels do not change materially over the sample period.

Table 4.2: One-Minute Interval Data Set

Properties of Nifty and Midcap Logarithmic Series (LN and LM) and Nifty and Midcap Log Returns (LRN and LRM)

Variable	LN	LM	LRN	LRM
Maximum Value	7.113	7.592	0.010	0.004
Minimum Value	7.012	7.522	-0.006	-0.003
Mean	7.070	7.560	0.0000	0.0000
Std. Deviation	0.024	0.015	0.0006	0.0005
Skewness	-0.804	-0.167	2.624	0.579
Excess Kurtosis	-0.319	-0.344	39.803	7.278
Jarque-Bera Test [(a)]	332.5 ***	28.4 ***	199,395 ***	6,719 ***
ADF Test Statistics (Excluding Trend) [(b)]:				
ADF (1)	-1.63	-1.06	-31.93	-32.29
ADF (5)	-1.65	-1.26	-20.80	-18.29
ADF (10)	-1.63	-1.28	-15.72	-15.13
95% Critical Value	*-2.86*	*-2.86*	*-2.86*	*-2.86*
ADF Test Statistics (Including Trend) [(b)]:				
ADF (1)	-0.91	-1.63	-31.96	-32.29
ADF (5)	-1.01	-1.91	-20.84	-18.28
ADF (10)	-0.93	-1.94	-15.78	-15.13
95% Critical Value	*-3.41*	*-3.41*	*-3.41*	*-3.41*

The above statistics are based on a time series of 2970 (price level) observations. Statistical significance at the 99%, 95% and 90% level of confidence is denoted by ***, ** and * respectively.

(a) The Jarque-Bera test for normality, is $\chi^2(2)$ distributed. The critical values are 9.21, 5.99 and 4.61, for the 99%, 95% and 90% confidence levels respectively, rejecting the null hypothesis of a normal distribution.

(b) The Augmented Dickey-Fuller statistics, test the null hypothesis of a unit root. The ADF(n) statistic is the t-ratio of ρ in the model

$\Delta X_t = \alpha + \rho\delta t - \rho X_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta X_{t-i} + \varepsilon_t$, t=1,...,z. The 95% critical values of the test are shown in MacKinnon (1991). The ADF tests do not reject the null hypothesis of a unit root for the logarithmic series. The null hypothesis of a unit root is rejected when considering the logarithmic returns.

Table 4.3: Average Trading Frequencies for Nifty and Midcap Shares

	Nifty Shares		Midcap Shares	
	Av. # Trades per Share	Av. Waiting Time (seconds)	Av. # Trades per Share	Av. Waiting Time (seconds)
15 June '99	3181	6.2	956	20.7
17 June '99	3798	5.2	858	23.1
21 June '99	3081	6.4	1034	19.1
23 June '99	3568	5.5	989	20.0
25 June '99	3180	6.2	965	20.5

The table shows the average number of transactions for the shares included in the Nifty and Midcap indices for five different trading days. Assuming that these transactions occur evenly throughout a trading day of five and a half hours, one can estimate the average waiting time – i.e. the average interval between trades.

Table 4.3 shows that the Nifty index is more liquid than the Midcap, in line with our expectations. On average, there is a waiting time of around 6 seconds in between trades for the shares included in the Nifty index, while the waiting time for the shares in the Midcap index is around 20 seconds. This implies that each of the index observations is "outdated" by around 6 seconds and 20 seconds respectively. In estimating the average waiting time, it was assumed that trades occur evenly throughout the day. This is not usually a realistic assumption – according to Shah and Sivakumar (2000) NSE trading tends to peak at the end of the day. This implies that during some periods, the average waiting time will decrease or increase; and in the latter case the non-synchronous trading effects become more pronounced.

Given that non-synchronous trading effects are mainly caused by the less liquid stocks, it also makes sense to look at the waiting time statistics of the less liquid shares in the respective indices. The waiting time statistics of the ten least frequently traded shares in each index are shown in Table 4.4. The table shows that one quintile of the information which is used in estimating Nifty observations is at least five minutes old. Similarly, Midcap observations are based on a data set, a quintile of which is around ten minutes old.

Thus, we may now re-formulate our expectations more specifically. Firstly, one may expect that the Midcap index should appear "less efficient" than the Nifty index, in the sense that we should obtain an indication that Midcap returns may be predicted to some degree from Nifty returns. This "inefficiency" is partly the result of non-synchronous trading, and the study aims to infer whether the predictability is more attributable to non-synchronous trading effects or actual delayed adjustments of traders' expectations. Secondly, one may also expect non-synchronous trading effects to be more pronounced in the high-frequency data set, following the notion that trading peaks at the end of the day, implying that closing prices should be based on reasonably current information.

Table 4.4: Average Trading Frequencies for Nifty and Midcap Least Frequently Traded Shares

	Nifty (Least Traded) Shares		Midcap (Least Traded) Shares	
	Av. # Trades per Share	Av. Waiting Time (minutes)	Av. # Trades per Share	Av. Waiting Time (minutes)
15 June '99	73	5	42	8
17 June '99	66	5	26	13
21 June '99	73	5	31	11
23 June '99	86	4	51	7
25 June '99	71	5	32	10

The table shows the average number of transactions for the ten least frequently traded shares included in the indices. Statistics for five different trading days are shown. Assuming that these transactions occur evenly throughout a trading day of five and a half hours, one can estimate the average waiting time – i.e. the average interval between trades.

4.5 Pesaran-Timmermann Tests

We now turn to the first predictability investigation through Pesaran-Timmermann (1992) tests. Given that this procedure is essentially a test on the signs, rather than the magnitude of a time series, it does not matter whether it is applied to simple returns or log returns. Pesaran-Timmermann tests were conducted not only on the contemporaneous relationship between the indices, but also on the relationship between the change of an index at time t with the lagged changes of the other index.

Table 4.5 shows Pesaran-Timmermann statistics for both the daily and intra-day data series. At both frequencies, the Nifty and Midcap indices tend to contemporaneously move in the same direction, as witnessed by the highly significant statistics of 20.28 for the daily data and 18.83 for the intra-day data. Assuming that the difference between these statistics is not due to the different sample periods, the lower test statistic for the high frequency data set, may indicate that non-synchronous trading effects are more evident in high frequency data. Despite this, one should note that the difference in test statistics is not so important at this level of significance.

Inspecting the Pesaran-Timmerman statistics for the daily data set in more detail, both the contemporaneous and the first lag are significant in predicting the change direction of the other index. The significant contemporaneous relationship implies that the indices tend to move in the same direction, as may be reasonably expected. Ignoring the other significant lags for the time being, we may note that the Nifty and Midcap indices are more or less equally relevant for predicting the direction change of the other index. This implies that the difference in liquidity in between the daily data sets is not resulting in differing degrees of predictability. We may thus assume that this predictability effect is not the result of non-synchronous trading or differing degrees of liquidity. One possible explanation might be "runs" in the data, whereby each of the indices changes successively in the same direction over a period of days. Data runs do not necessarily contradict the efficient market hypothesis given that longer runs may be considered as a normal feature when analysing a series that may be classified as a random walk with drift.

The other significant lagged observations in the daily data set are the third Midcap lag, and the fourteenth Nifty lag. As regards the latter, there might be no economic reason why the current direction change of the Midcap is affected by the Nifty direction change of 14 days ago, and thus we may treat it as a rogue observation. The third Midcap lag direction change is significant in predicting the current Nifty direction change. One might again think of this as a rogue observation, yet there might be an economic reason why the lagged change direction of the smaller capitalisation index affects the current change direction of the index of larger companies. Whilst causality is usually assumed to run from larger stocks to smaller ones, there might be a case for arguing that smaller companies may affect larger ones as well. Some events may impact to a higher degree on smaller companies. These may include concessions which aim to reduce the regulatory burden on smaller companies, or a sudden reduction in local consumer demand, when smaller companies rely to a larger extent on domestic trade. In such cases, one might argue that these events are immediately reflected in the prices of smaller company stocks. Yet, one may still expect that the fluctuations eventually spill over to larger company stocks. For instance, a positive news item might make smaller companies more optimistic and therefore they would increase their trading with larger companies, say those who supply them with raw materials. Therefore it might be plausible that Midcap shocks eventually spill over to Nifty prices. Yet, Table 4.5 indicates that it takes about 3 days for market participants to price in these effects, and it may be debatable whether this is a short enough period to be consistent with such an adjustment.

Table 4.5: Pesaran-Timmermann Statistics

	Daily Data				Intra-Day Data			
Lag (a)	$S(M_t,N_{t-a})$		$S(N_t,M_{t-a})$		$S(M_t,N_{t-a})$		$S(N_t,M_{t-a})$	
0	20.28	***	20.28	***	18.83	***	18.83	***
1	3.99	***	3.65	***	13.41	***	11.61	***
2	-0.31		0.60		8.18	***	3.37	***
3	1.60		2.97	***	5.96	***	0.34	
4	1.58		1.69		4.47	***	0.87	
5	0.19		0.30		5.19	***	0.52	
6	-1.72		-1.49		3.92	***	-1.08	
7	-0.55		-0.44		1.95	*	0.48	
8	-0.35		1.07		0.35		-1.74	
9	1.16		1.21		-0.36		-2.42	
10	1.36		-0.01		0.90		-1.56	
11	0.99		0.13		0.67		-2.49	
12	0.91		0.73		-0.31		-0.89	
13	0.31		0.82		0.23		-1.10	
14	2.06	**	-0.75		-0.71		-0.79	
15	0.37		-0.56		-0.95		-0.51	
16	0.58		0.45		-1.82		-1.63	
17	0.15		0.82		-0.11		-0.99	
18	-0.17		0.85		-1.52		-1.56	
19	-1.06		-0.04		-0.14		-1.25	
20	-0.91		0.22		-0.71		-1.75	
21	-1.28		-0.15		0.82		0.11	
22	-0.56		-0.47		1.06		-0.68	
23	0.50		0.37		0.27		-0.66	
24	-0.50		1.43		1.32		0.72	
25	0.50		0.60		1.00		1.59	
26	0.02		-1.15		1.61		2.01	**
27	1.03		0.49		1.12		3.51	***
28	-0.44		0.52		1.87	*	0.42	
29	-0.01		-0.32		0.27		-1.33	
30	-0.44		-0.06		0.84		-0.87	

The table shows Pesaran-Timmermann Test Statistics (S) for the relationship between the Nifty Index (N) and the Midcap Index (M). Both contemporaneous and lagged relationships are investigated. Being normally distributed, the critical values for the test are: 2.58, 1.96 and 1.65 for the 99%, 95% and 90% level of confidence respectively. Significance at these levels of confidence is denoted by *** (99%), ** (95%) and * (90%).

When considering the lagged relationships in the high-frequency data, we note that both indices tend to move in synchronicity with the other index and a number of lags. Given that the first two lagged change directions are significant in both cases, we may again attribute this to data runs. At such high frequencies it may not be realistic to expect abrupt price changes given that as new information becomes available it is plausible that "old" limit orders do not get cancelled immediately and are "picked off"; i.e. they trade against an order that was submitted by a trader with more updated information. In this way the stock would still trade at the "old" price, despite the availability of new information.

Yet, the Nifty change directions remain significant for a further five lags and this suggests that the Nifty leads the Midcap as may be expected. This might be due to non-synchronous trading effects where the less liquid stocks appear to take longer to adjust to news, given that they trade less frequently. The remaining significant lags in the high frequency data set, may either be considered as rogue observations, or they may also be consistent with feedback effects running from the Midcap to the Nifty index.

Overall, these statistics indicate that the Nifty index leads the Midcap at high frequency data, while the indices tend to move almost contemporaneously at daily frequency. This may imply that the Midcap index appears to adjust more slowly – but not slowly enough to obtain clear predictability at daily frequency. This seems in line with our prior expectations: "causality" mainly runs from the Nifty to Midcap, and (at least) part of this predictability is the result of non-synchronous trading effects, which become more pronounced in the high frequency data set.

4.6 Granger-Causality Tests

4.6.1 Daily Interval Data

A preliminary 24 order VAR was estimated (using the log returns series) in order to select the optimal order of the VAR. As shown in Appendix 4.2, both the Akaike Information Criterion and the Schwarz Bayesian Criterion selected a VAR(1) model, yet the log-likelihood ratio statistics rejected all orders less than 16. In view of this, two VAR models were estimated: a VAR(1) and a VAR(16). The former model was deemed superior on the basis of a higher System Log Likelihood Ratio, higher Log Likelihood Ratios for the individual equations, higher F-statistics, and higher Akaike Information Criteria and Schwarz Bayesian Criteria, as shown in Appendix 4.3. Besides, it is not clear on practical grounds why an index shock taking place on day t, should still affect the price series on day $t+16$.

When inspecting the largest error terms of the VAR(1) regressions, it was not apparent that errors tended to occur on any particular day of the week. If we hypothesise that more volatile returns are realised on Mondays, this would imply that the VAR(1) regressions would perform badly in forecasting the Monday return, as well as the Tuesday returns (given that the Monday information is then used to forecast the Tuesday return). Therefore, one may expect that the Monday effect would result in larger forecast errors for Mondays and Tuesdays. The largest 40 error terms for each of the VAR regressions were inspected, but the Monday and Tuesday errors did not particularly outnumber those of other trading days.[28] This is in line with the empirical results of Choudhry (2000) who found that the change in volatility on Mondays was not significant on the Indian market.

The individual regressions of the estimated VAR(1) model and diagnostic statistics, are shown in Table 4.6 Panels A and B together with error plots and histograms. The LM statistics indicate that error terms are heteroskedastic. This may be attributed to exogenous factors which are not being captured by the model. Given that our main interest is the relationship between the indices, this might not be particularly problematic as long as the omitted variables do not lead to spurious results.

In both equations, the coefficients through which one can infer any lead-lag relationship between the indices are insignificant, as shown in Table 4.6. The most "significant" coefficient in the respective regressions is the lag of the dependent variable. Despite this, the F-tests reject the null hypothesis that the joint coefficients are equal to zero in case of both regressions; yet this may be probably attributed to the lagged dependent variable, rather than the lag of the other index.

In order to investigate further, Granger non-causality tests were conducted on the Nifty and Midcap Log Return series in the system of equations, as detailed in Table 4.6 Panel B. This methodology tests the null hypothesis of no causality, and the tests did not permit the rejection of the null hypothesis of no-causality for both variables.

A Log Likelihood Ratio (LR) Statistic was computed as detailed in Table 4.6 Panel B, and this permitted the rejection of the null hypothesis that the contemporaneous covariance between the fluctuations in the log returns series is equal to zero.

[28] A histogram is tabulated in Appendix 4.4.

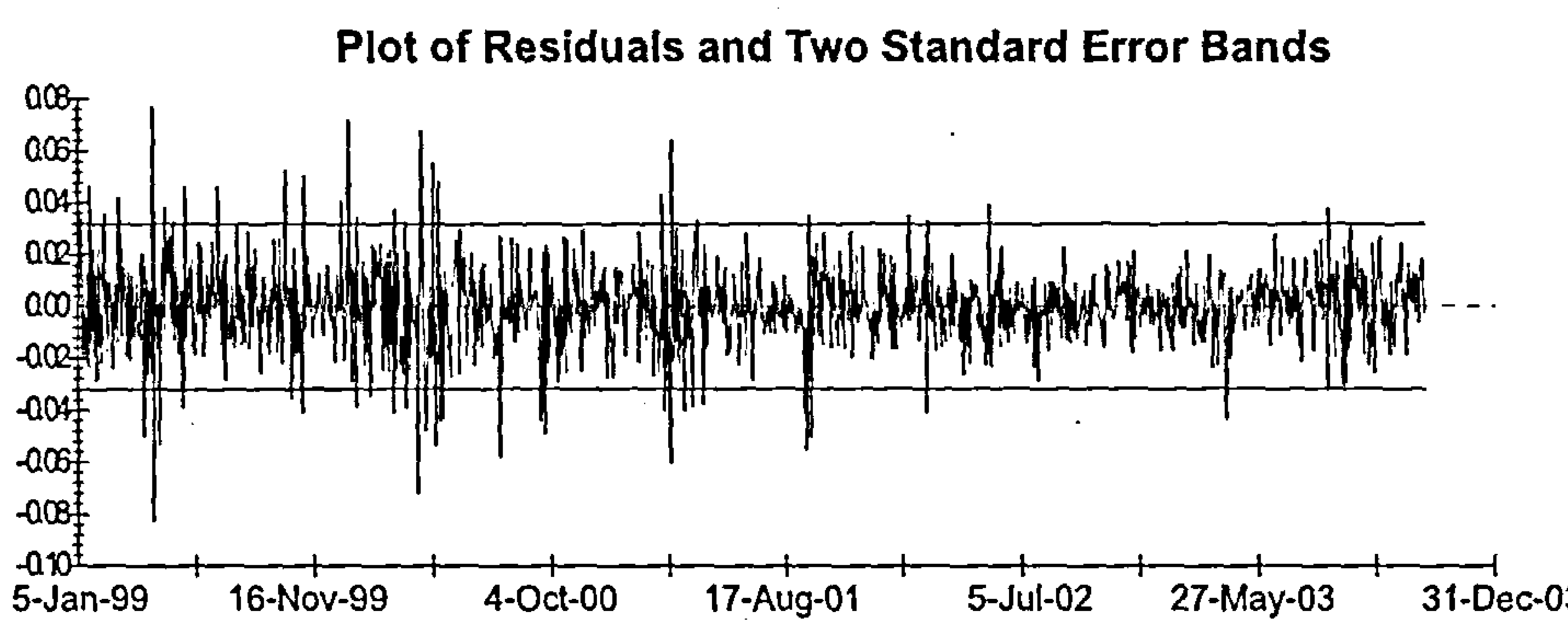
Table 4.6 Panel A: OLS Regression Coefficients and Error Plots for Nifty Equation in the VAR (daily data).

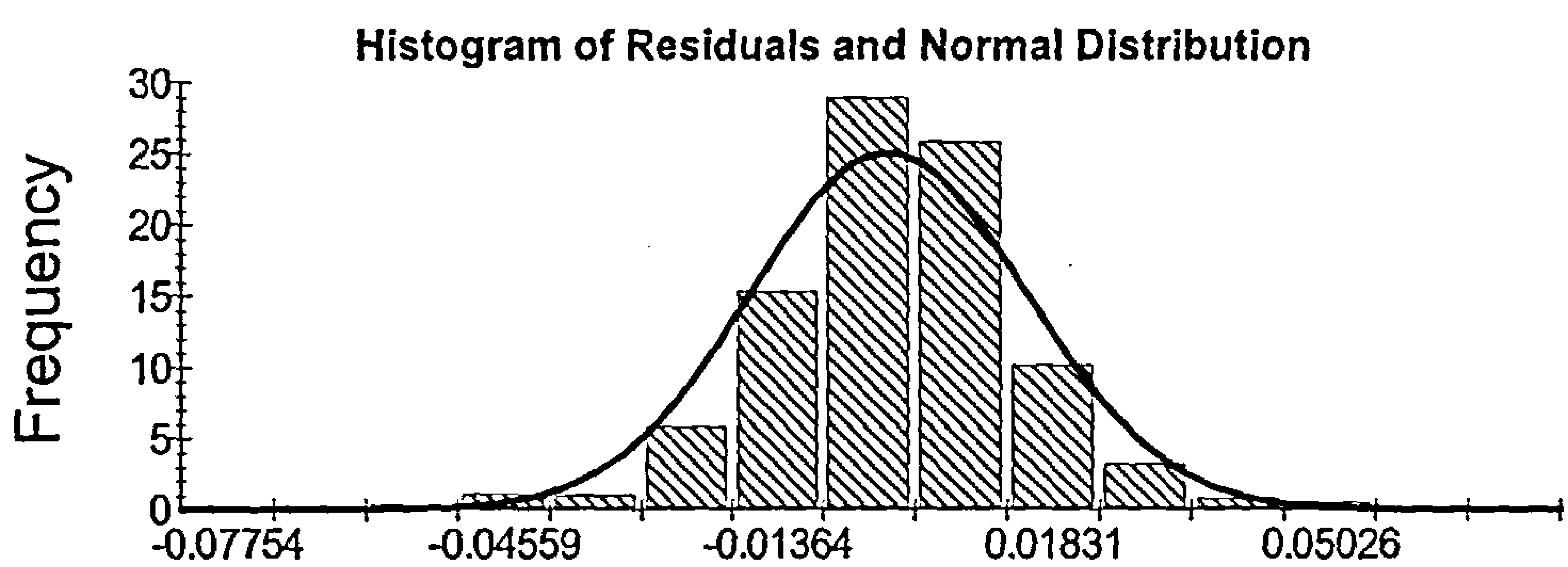
Regressor	Intercept	Lagged Nifty	Lagged Midcap
Coefficient	0.0005	0.0575	0.0136
T-Ratio	(1.21)	(1.24)	(0.37)

Number of Observations	1255	R-Bar-Squared	0.004
S.E. of Regression	0.016	F-statistic [a]	3.257
Residual Sum of Squares	0.318	Equation Log-likelihood	3416.0
Residual Heteroskedasticity [b]	56.83	System Log-likelihood	7168.3

a) The F-statistic is F-distributed with 2 and 1252 degrees of freedom. The 95% critical value is 3.00, rejecting the null hypothesis that all the regressors (except the intercept) are zero.

b) The residual heteroskedasticity test is based on the regression of squared residuals on squared fitted values (Godfrey, 1978). It is $\chi^2(1)$ distributed with a critical value of 6.635 for a one tailed test at the 99% confidence level. The statistic rejects the null hypothesis that error terms are serially uncorrelated.





Overall, these results are in line with the inferences obtained through the above Pesaran-Timmermann tests, that there is only a weak lead-lag relationship (if at all) between the Nifty and Midcap indices, when sampled at daily intervals. It might be more accurate to postulate a contemporaneous relationship between the indices at this frequency, as inferred through the LR test and the Pesaran-Timmermann test. Again, this suggests that the differing liquidity levels in between indices do not lead to pronounced non-synchronous trading effects which may be gauged through lead-lag effects in daily data. This might be caused by the typical trading peak at the end of the day, which implies that the closing index observations are based on reasonably current information.

Table 4.6 Panel B: OLS Regression Coefficients, and Error Plots for Midcap Equation in the VAR (daily data) and Tests on the VAR System.

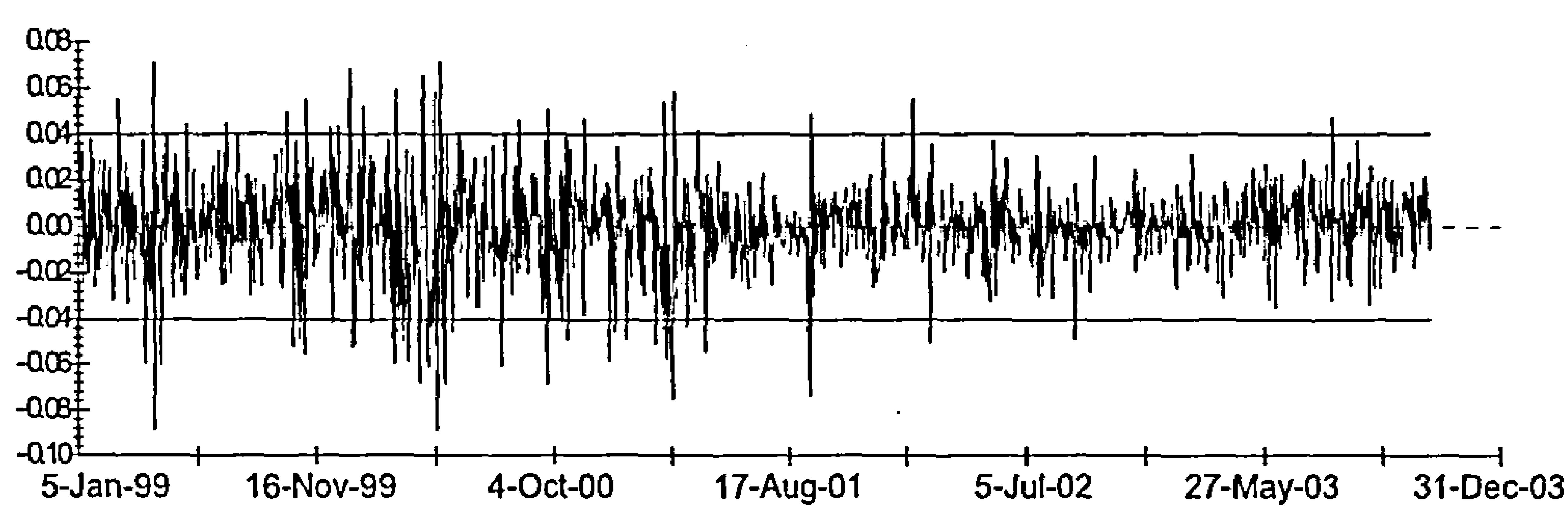
Regressor	Intercept	Lagged Nifty	Lagged Midcap
Coefficient	0.0005	-0.0244	0.1682
T-Ratio	(0.9410)	(0.4173)	(3.6694)

Number of Observations	1255	R-Bar-Squared	0.022
S.E. of Regression	0.020	F-statistic [a]	15.103
Residual Sum of Squares	0.506	Equation Log-likelihood	3124.4
Residual Heteroskedasticity [b]	145.7	System Log-likelihood	7168.3

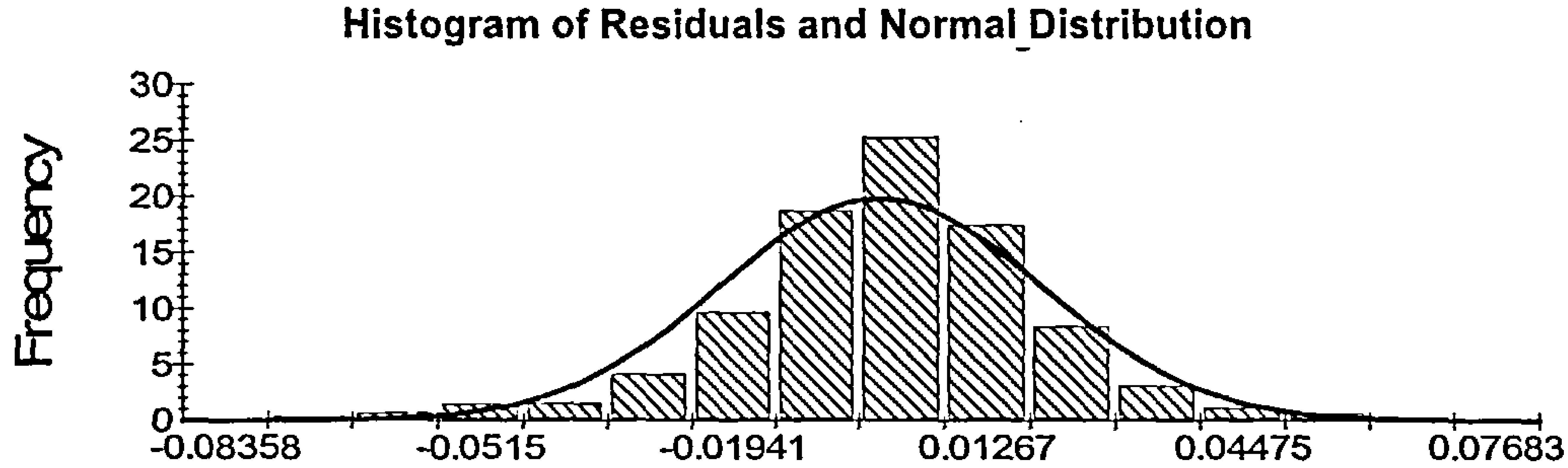
a) The F-statistic is F-distributed with 2 and 1252 degrees of freedom. The 99% critical value is 4.61, rejecting the null hypothesis that all the regressors (except the intercept) are zero.

b) The residual heteroskedasticity test is based on the regression of squared residuals on squared fitted values (Godfrey, 1978). It is $\chi^2(1)$ distributed with a critical value of 6.635 for a one tailed test at the 99% confidence level. The statistic rejects the null hypothesis that error terms are serially uncorrelated.

Plot of Residuals and Two Standard Error Bands



Histogram of Residuals and Normal Distribution



Granger Non-Causality Tests: When testing the null hypothesis that the coefficient of lagged Nifty in the Midcap equation is zero, a statistic of 0.17453 is obtained. When testing the null hypothesis that the coefficient of lagged Midcap in the Nifty equation is zero a statistic of 0.13989 is obtained. Being $\chi^2(1)$ distributed, with a critical value of 3.841 (one-tailed; 95% confidence level), the former tests do not permit the rejection of the null hypothesis of no-causality for both variables.

Log Likelihood Ratio (LR) Statistic: The LR Statistic tests the null hypothesis that contemporaneous covariance between fluctuations in the series is equal to zero. Log-Likelihood statistics for the VAR system, Nifty and Midcap Equations (estimated independently through OLS) are shown in Panels A and B of this table. LR (H_0:H_1) ratio is computed as [2 (7168.3 - 3416.0 - 3124.4)] and is equal to 1255.8. The test is $\chi^2(2)$ distributed, with a 99% critical value of 9.21. We thus reject the null hypothesis that shocks are contemporaneously uncorrelated.

6.2 High Frequency Data

The above procedure was repeated using the high frequency data set.

A preliminary 24 order VAR was estimated (using the log returns series) in order to select the optimal order of the VAR. As shown in Appendix 4.5, the Akaike Information Criterion selected a VAR(9) model, whilst the Schwarz Bayesian Criterion selected a VAR(3) model. Yet, the log-likelihood ratio statistics rejected all orders which were less than 7, and therefore an order 9 VAR was selected.

The diagnostics for this initial VAR(9) model showed problems in terms of normality and heteroskedasticity. A histogram of the error terms showed that the deviations from normality are not particularly problematic – the histograms were peak-shaped and therefore most of the error terms were close to zero.

When plotting the error terms, it became apparent that large errors tended to occur at approximately equally-spaced intervals and this partly explains the heteroskedasticity of the error terms. The larger error terms tend to occur on the opening of the trading day – particularly at the first two observations. This is not surprising since a higher amount of news is priced during the first observation following the overnight interval. The lagged initial return of the trading day is then used to explain the second return during the trading day in the VAR system, and the first "unusual observation" leads to a particularly weak forecast for the return realised during the second minute.

Thus a dummy variable was created taking a value of 1 during the first two observations of each trading day. A log-likelihood ratio test on the deletion of the dummy yielded a statistic of 408.35; being $\chi^2(2)$ distributed the test indicates that the dummy is highly significant. The "dummy version" of the VAR resulted in regression equations with a higher R^2 and Adjusted R^2, yet the error term remained non-normal and heteroskedastic. As regards the latter, the plot of the error terms still showed regularly-spaced errors. This may be attributed to the fact that in some cases, the large error at the opening occurred at the third, fourth, ...sometimes tenth observation for the day. The dummy variable does not account for these observations. However, modifying the dummy variable to include the first ten observations of each day would "dilute" the dummy with smaller error terms, and this might reduce the effectiveness of the dummy.

Table 4.7 Panel A: Nifty and Midcap VAR Coefficients and Tests on the VAR system (one-minute frequency data).

	Nifty Regression			Midcap Regression		
Regressor	Coefficient		T-Ratio	Coefficient		T-Ratio
LRN(-1)	0.203	***	(10.51)	0.241	***	(16.26)
LRN(-2)	0.012		(0.61)	0.077	***	(4.96)
LRN(-3)	0.010		(0.50)	0.075	***	(4.84)
LRN(-4)	-0.010		(0.49)	0.019		(1.21)
LRN(-5)	0.013		(0.64)	0.023		(1.47)
LRN(-6)	-0.030		(1.50)	0.034	**	(2.18)
LRN(-7)	0.048		(2.37)	0.011		(0.72)
LRN(-8)	0.000		(0.01)	-0.045	***	(2.90)
LRN(-9)	0.015		(0.77)	0.039	***	(2.59)
LRM(-1)	0.162	***	(6.06)	0.027		(1.31)
LRM(-2)	-0.036		(1.35)	-0.080	***	(3.92)
LRM(-3)	0.041		(1.53)	0.031		(1.52)
LRM(-4)	-0.028		(1.06)	-0.011		(0.53)
LRM(-5)	0.033		(1.26)	-0.010		(0.50)
LRM(-6)	-0.028		(1.06)	0.031		(1.51)
LRM(-7)	-0.078	***	(2.97)	-0.042	**	(2.07)
LRM(-8)	-0.002		(0.06)	0.036	*	(1.78)
LRM(-9)	-0.032		(1.28)	0.011		(0.55)
Intercept	0.000		(0.45)	0.000		(0.69)
O (dummy)	0.003	***	(19.18)	0.000		(1.29)

The first column shows the regressor, where LRN and LRM stand for Nifty and Midcap Log Return, whilst O is a dummy variable which takes the value of 1 for the first 2 observations of the trading day and zero otherwise. Lags are denoted as (-1), (-2), etc. For both the Nifty and Midcap equations, the table shows the regression coefficients and T-ratios in brackets. ***, ** and * denote statistical significance at the 99%, 95% and 90% levels of confidence respectively.

Granger Non-Causality Tests: When testing the null hypothesis that the coefficients of lagged Nifty in the Midcap equation are zero, a statistic of 51.6 is obtained. When testing the null hypothesis that the coefficients of lagged Midcap in the Nifty equation are zero a statistic of 328.1 is obtained. Being $\chi^2(9)$ distributed, with a critical value of 21.67 (one-tailed; 99% confidence level), the former tests permit the rejection of the null hypothesis of no-causality for both variables.

Log Likelihood Ratio (LR) Statistic: The LR Statistic tests the null hypothesis that contemporaneous covariance between fluctuations in the series is equal to zero. Log-Likelihood statistics for the VAR system, Nifty and Midcap Equations (estimated independently through OLS) are shown in Panel B of this table. LR (H_0:H_1) ratio is computed as [2 (36954 - 17915 - 18705)] and is equal to 666. The test is $\chi^2(19)$ distributed, with a 99% critical value of 36.19. We thus reject the null hypothesis that shocks are contemporaneously uncorrelated.

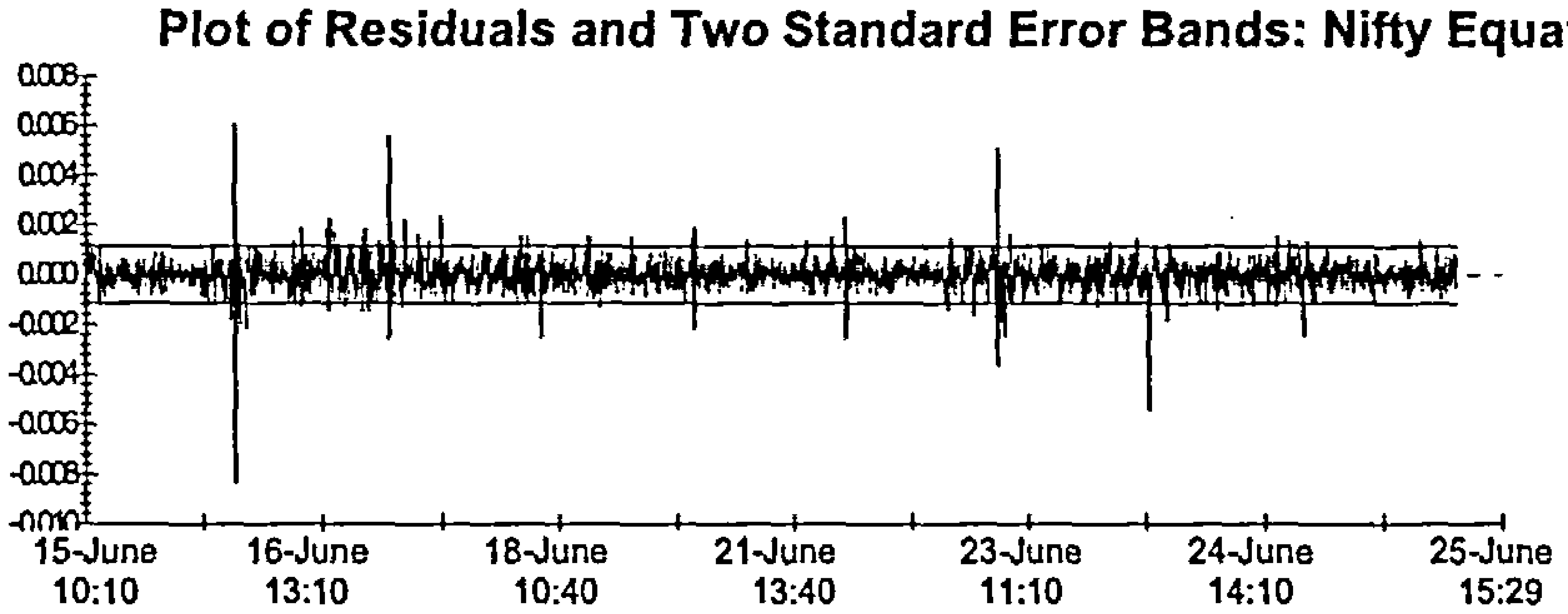
Table 4.7 Panel B: Diagnostic Statistics and Error Plots for the VAR System (one-minute frequency data)

	Nifty equation	Midcap equation		Nifty equation	Midcap equation
Number of Observations	2960	2960	R-Bar-Squared	0.185	0.162
S.E. of Regression	0.0006	0.0004	F-statistic [a]	36.34	31.02
Residual Sum of Squares	0.0010	0.0006	Equation Log-likelihood	17915	18705
Residual Heteroskedasticity [b]	975.1	65.61	System Log-likelihood	36954	36954

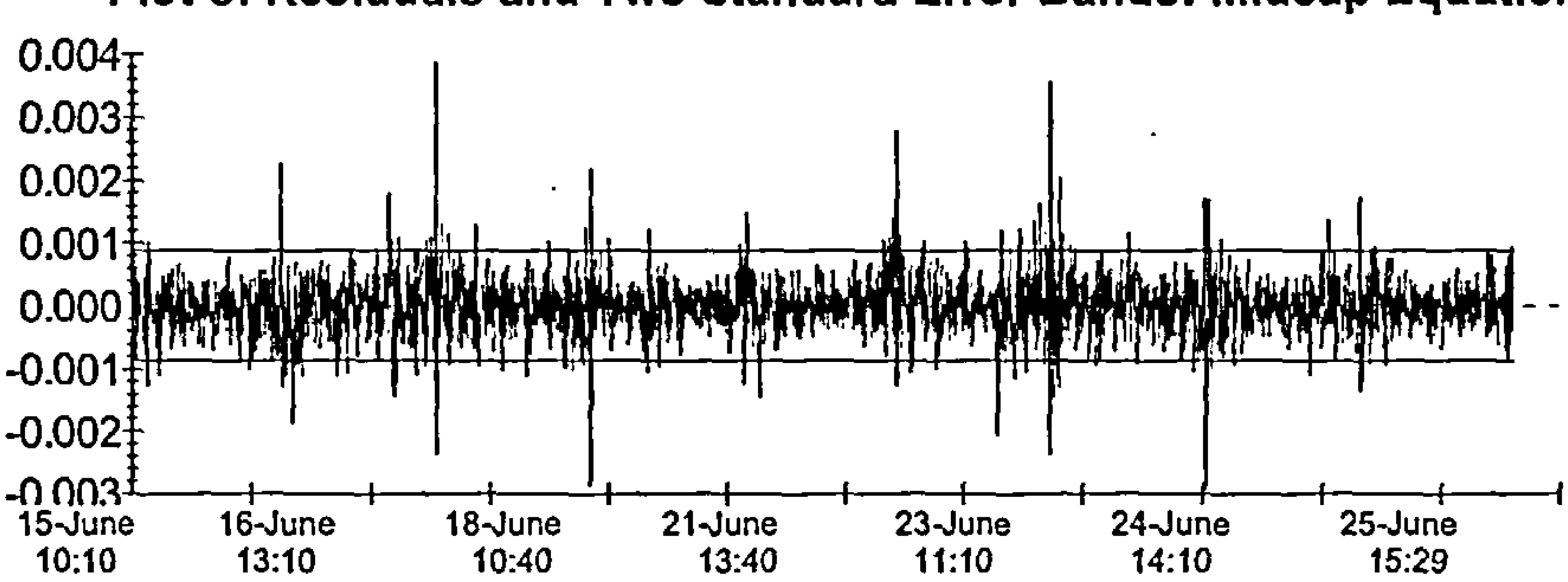
a) The F-statistic is F-distributed with 19 and 2940 degrees of freedom. The 99% critical value is 1.96, rejecting the null hypothesis that all the regressors (except the intercept) are zero for both equations.

b) The residual heteroskedasticity test is based on the regression of squared residuals on squared fitted values (Godfrey, 1978). It is $\chi^2(1)$ distributed with a critical value of 6.635 for a one tailed test at the 99% confidence level. The statistics for both equations reject the null hypothesis that error terms are serially uncorrelated.

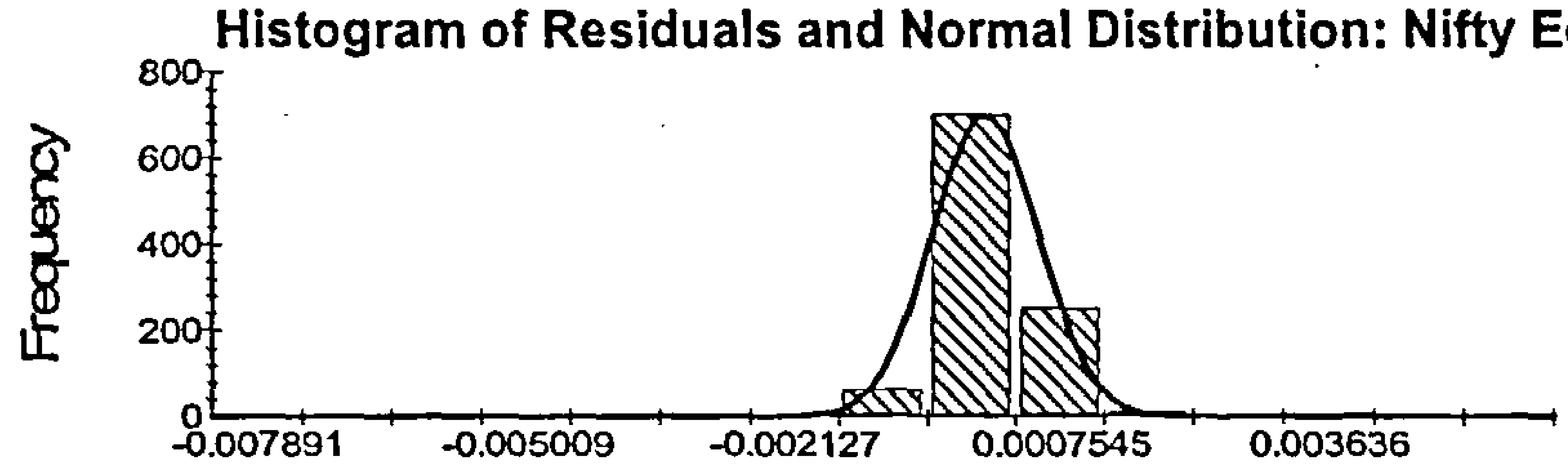
Plot of Residuals and Two Standard Error Bands: Nifty Equation



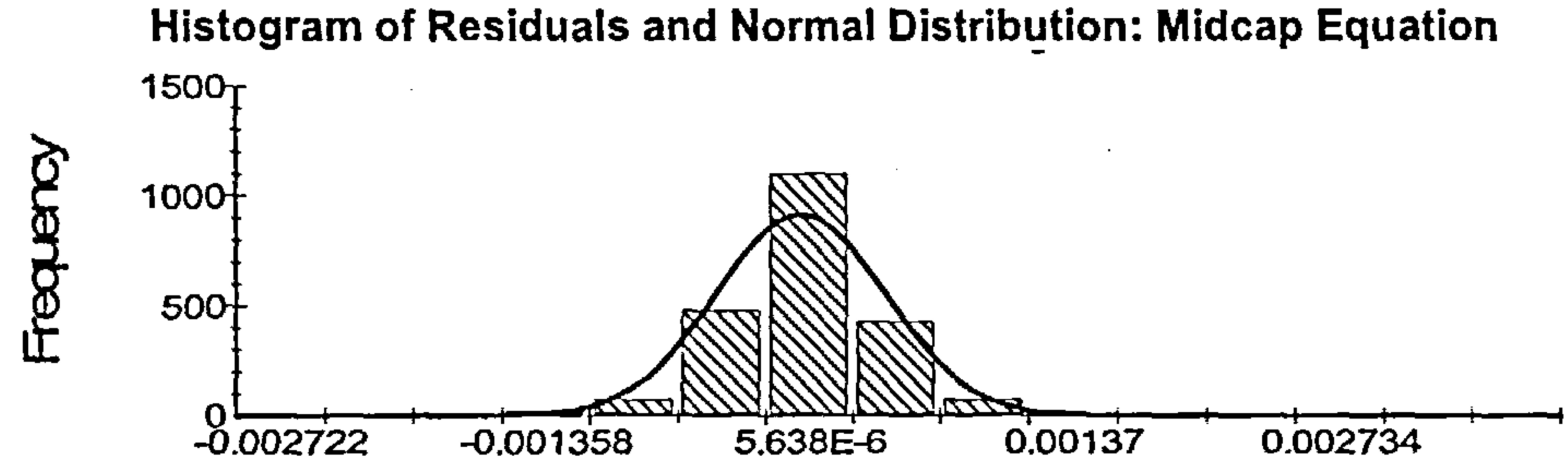
Plot of Residuals and Two Standard Error Bands: Midcap Equation



Histogram of Residuals and Normal Distribution: Nifty Equation



Histogram of Residuals and Normal Distribution: Midcap Equation



Granger non-causality tests were conducted on the Nifty and Midcap Log Return series in the system of equations, as detailed in Table 4.7 Panel A. The tests permitted the rejection of the null hypothesis of no-causality for both series at the 99% confidence level. A Log Likelihood Ratio (LR) Statistic was computed as detailed in Table 4.7 Panel A. The statistic strongly rejects the null hypothesis that the contemporaneous covariance between the fluctuations in the log returns series is equal to zero.

Thus we may assume the presence of Granger-Causality and contemporaneous effects between the indices as sampled at one-minute intervals and propose a system of equations as shown in Table 4.7 Panel A. Diagnostic statistics and error plots are shown in Table 4.7 Panel B.

The VARs fitted in this section, for the data sets at daily and one-minute frequency confirm the inferences from the Pesaran-Timmermann tests of the previous section. The strongest relationship is that at one-minute frequency, the Nifty index leads the Midcap and there is a tendency for a feedback effect from Midcap to Nifty. The indices tend to move more or less contemporaneously at daily frequency – and this is in line with the conclusions of Chiao, Hung and Lee (2004). The insignificance of any causality at daily intervals may be partly attributed to the surge in trading activity at the end of the day which reduces the degree of non-synchronicity. Yet, we should note that this result is in contrast to the finding of Poshakwale and Theobald (2004) who reported that there are lead-lag effects from larger to smaller Indian stocks when using daily data. The contrasting evidence may be partly reconciled by the use of more recent data in this study – possibly smaller stocks reacted more promptly to news in later years.

One possible explanation for the evidence gleaned so far, might be that market-wide information is first reflected in the Nifty index, which includes the most liquid stocks. Some minutes after this, the information is priced in the Midcap index, and we obtain a lead-lag relationship at high frequency intervals. This may be consistent with the fact that market participants tend to monitor the major stocks (the Nifty stocks) more closely, and therefore they first price in the new information in these stocks. Whether this conjecture is true or otherwise, the "extra waiting time" which is required for the Midcap stocks to trade (Tables 4.3 and 4.4), invariably results in non-synchronous trading effects in the high-frequency data set.

Yet, by the end of the day most of the new market-wide information would have been priced in both of the indices, and therefore only a contemporaneous relationship is detected when investigating relationships at daily frequency.

The Granger-Causality from Midcap to Nifty in the high-frequency data, may be consistent with the spillover effects from smaller to larger stocks (Section 4.5). The feedback effect from Midcap to Nifty is unlikely to be the result of non-synchronous trading, since the companies constituting the main index are more liquid than the smaller capitalisation companies. Thus, the evidence obtained so far is in line with our prior expectations that non-synchronous trading effects result in predictability, yet not *all* of the predictability is the result of non-synchronous trading.

4.7 Impulse Response Functions

We next generate Impulse Response Functions (IRFs) for respective shocks in the Nifty and Midcap indices, using the VAR system obtained for each data frequency. IRFs detect the response of particular variables to a shock in a given variable, and therefore they may be used to assess whether the "shocked variable" might be relevant in predicting the movements in the other variables. Section 4.7.1 deals with the responses to Nifty shocks, whilst Section 4.7.2 discusses the responses to Midcap shocks.

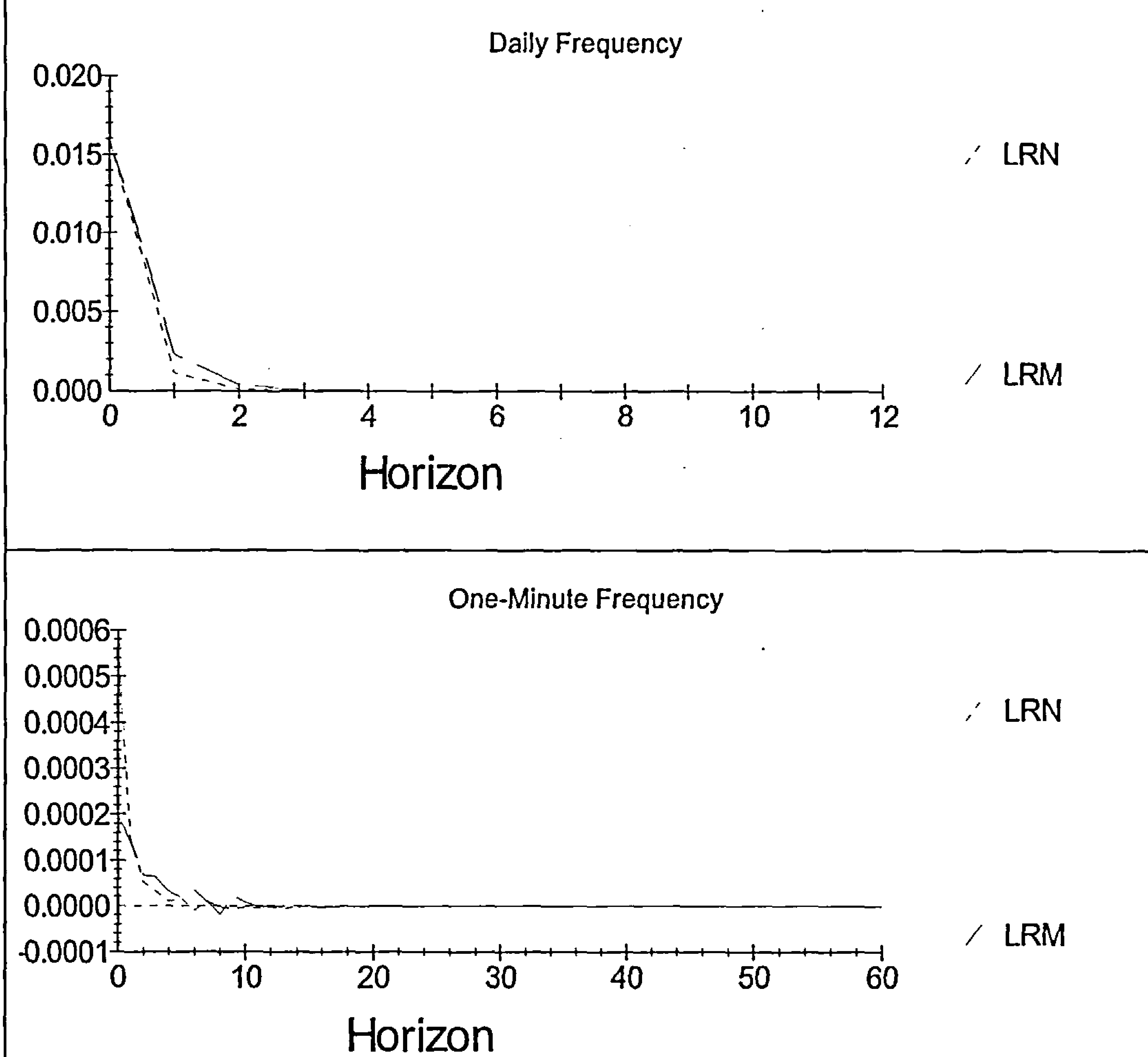
4.7.1 Responses to Nifty Shocks

IRFs showed that a given shock in the Nifty log return series affects the Midcap log return in the same direction. Being the first variable in the VAR, the Orthogonalised and Generalised IRFs for Nifty are identical (Pesaran and Shin; 1997). IRF plots for daily and one-minute frequencies respectively are shown in Figure 4.5, whilst Appendix 4.6 reports the actual IRF statistics.

In case of the daily data sets, the shocks practically die out within one day. This is in line with the notions that no high degree of causality may be expected when using this sampling frequency. In case of the high-frequency data sets, the shocks die out approximately within 10 minutes, since they are based on a VAR system of order 9.

For both data sets, when considering the latter part of the effect (i.e. just before the shocks die out) the effect on the Midcap is larger than that on the Nifty. In case of the high-frequency data set this may be attributed to the "lead-lag" relationship which partly emanates from non-synchronous trading effects. In case of the daily sets, the larger effect on the Midcap seems visible right from the initial part of the IRF.

Figure 4.5: Generalised and Orthogonalised IRFs following a Nifty Shock



The Generalised and Orthogonalised IRFs for a Nifty Shock are identical, since Nifty is the first variable in the VAR (Pesaran and Shin; 1997). LRN denotes the response of the Nifty Index, whilst LRM denotes the response of the Midcap Index.

The observation that a shock in variable x has a greater impact on variable y rather than on itself is rather unusual in empirical exercises involving IRFs. This may suggest that any actual causality effects which run from Nifty to Midcap are further amplified by non-synchronous trading effects. Yet, there might also be an additional explanation as to why a Nifty shock might lead to a higher Midcap shock, and this relates to the risks of the stocks. If we assume that the smaller companies are more risky, they should have higher *betas* and therefore should fluctuate more widely as compared to the larger company stocks. Thus, a given news item may have a higher impact on the Midcap rather than on the Nifty index. Given that this research does not account for news releases the results present an "illusion" that a Nifty shock results in a larger shock in the Midcap; yet the latter movement might be a response to news rather than a response to the Nifty shock itself.

4.7.2 Responses to Midcap Shocks

We now turn to the responses following a shock in the Midcap index. This time, the Orthogonalised and Generalised versions of the IRFs yielded differing results. Figure 4.6 shows the Orthogonalised IRFs whilst Figure 4.7 shows the Generalised IRFs. Actual statistics are shown in Appendix 4.7: Panel A (daily data set) and Panel B (high frequency data set).

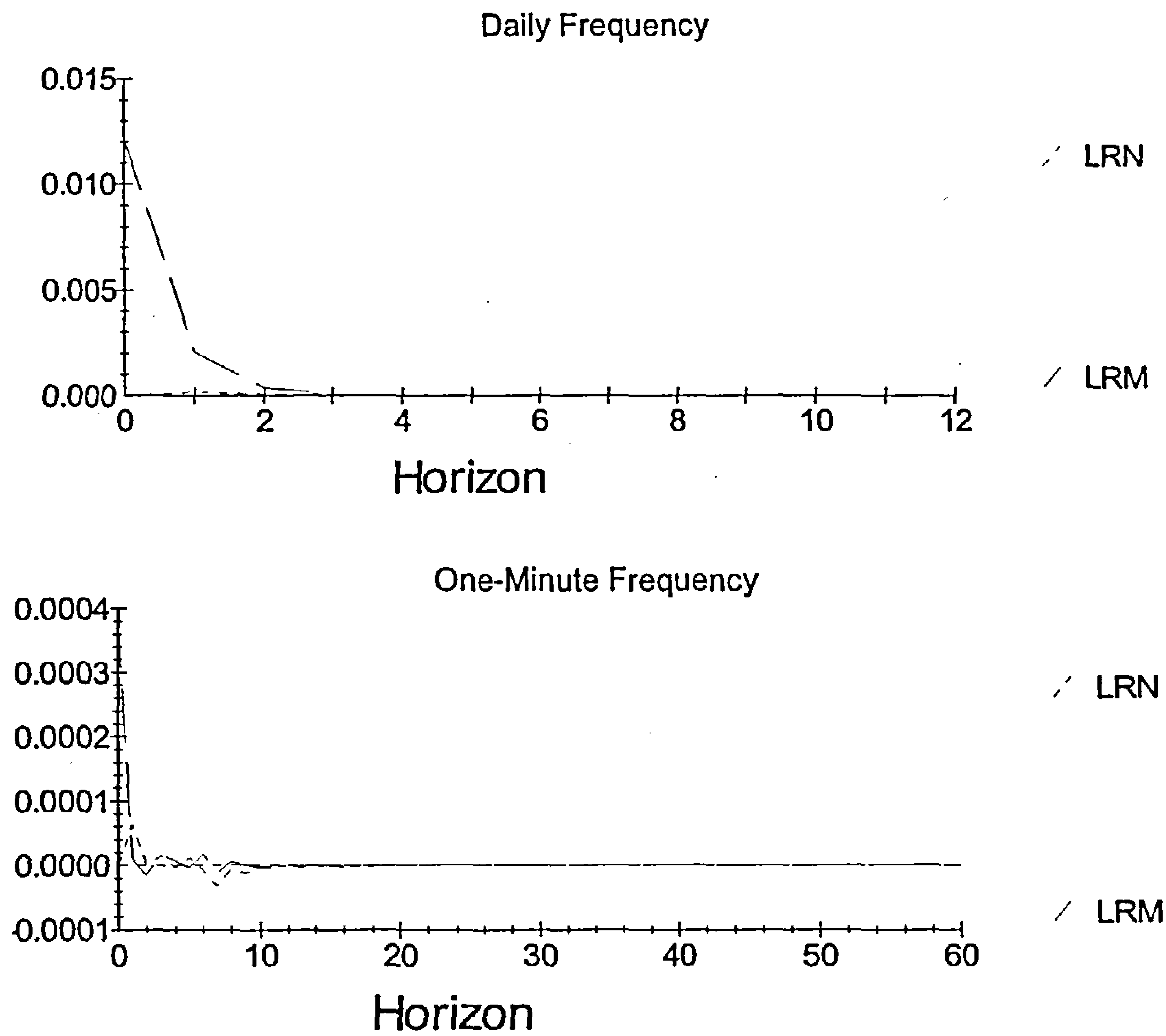
The Orthogonalised IRFs show that the Nifty index is practically unresponsive to Midcap shocks, especially when considering the daily data set.

The Generalised IRFs seem to indicate that the Nifty index responds to Midcap shocks. A shock in the Midcap leads to a Nifty fluctuation in the same direction which dies out after one day in case of the daily data set, and before 10 minutes in case of the high-frequency data set.

Given that Midcap stocks trade less frequently than Nifty stocks, we cannot attribute any predictability that runs from Midcap to Nifty to non-synchronous trading effects. Overall, the IRFs suggest the presence of a feedback effect from Midcap to Nifty, although this does not seem particularly pronounced.[29]

[29] Possible reasons why a small capitalization index may affect the main index were discussed in Section 4.5.

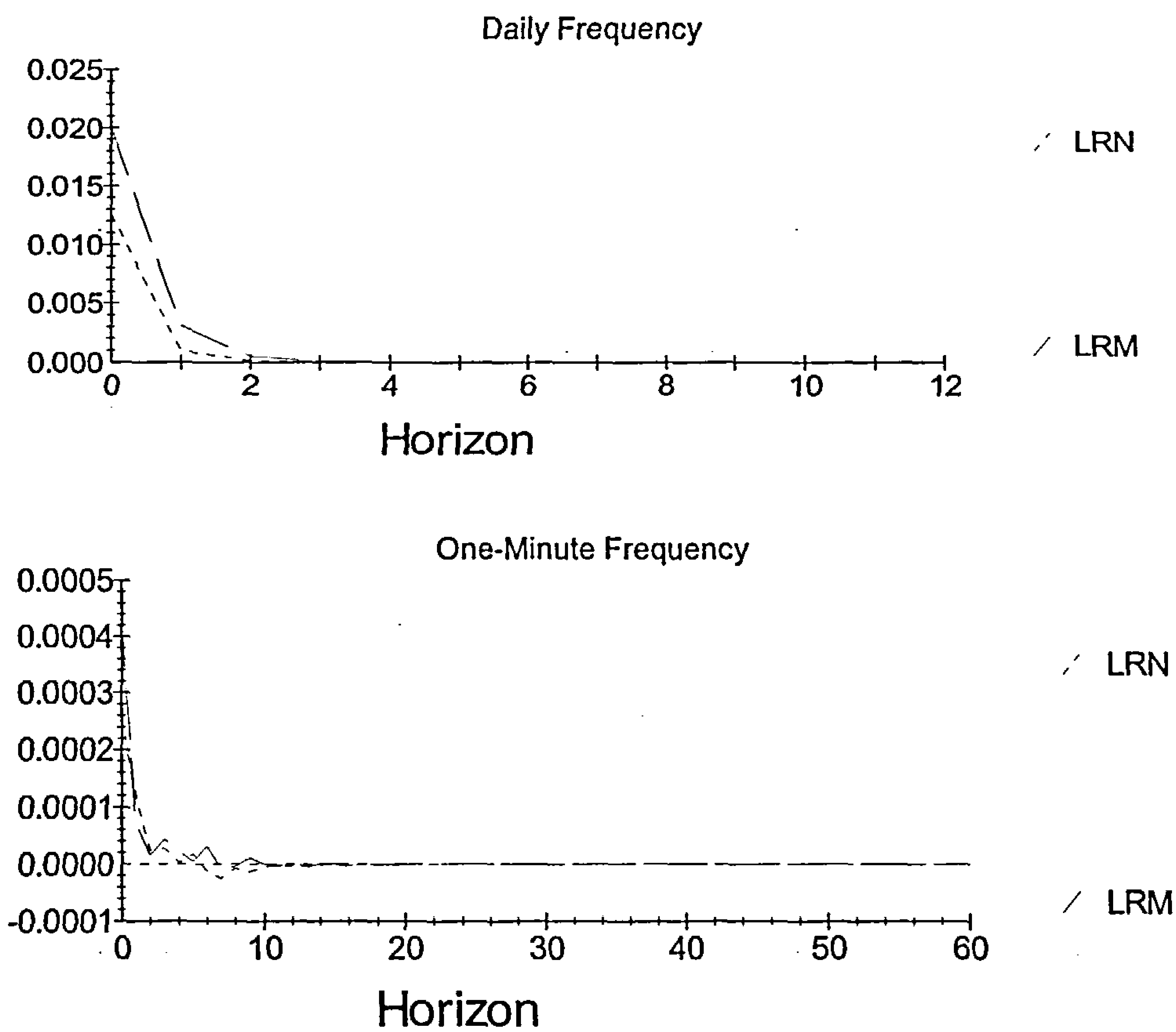
Figure 4.6: Orthogonalised IRFs following a Midcap Shock



LRN denotes the response of the Nifty Index, whilst LRM denotes the response of the Midcap Index.

Overall, the IRFs (together with the previous tests) suggest that the lead-lag effects which are present in the data are a combination of actual "causality" or delayed adjustments to news, and non-synchronous trading effects.

Figure 4.7: Generalised IRFs following a Midcap Shock



LRN denotes the response of the Nifty Index, whilst LRM denotes the response of the Midcap Index.

4.8 Inefficiency or Non-Synchronous Trading Effects?

Considering the above three predictability investigations, one observation which was consistently confirmed is that at high frequency intervals the Nifty index unambiguously leads the Midcap index. The "causality" from Nifty to the Midcap may be explained both by non-synchronous trading arguments and by the possibility that market participants do not adjust their expectations immediately since they do not follow lower-capitalisation companies as closely. A further elaboration on this argument may be inferred from the research of Niarchos and Alexakis (1998) in relation to the Greek Stock market. The authors argued that foreign investors tend to restrict their holdings in a particular category of shares. Since foreign investors are typically more sophisticated, the latter share category is more efficient.[30] Therefore, if in the case of NSE overseas investors restrict their holdings to the shares in the main index (which is quite plausible), one would expect Nifty to be more efficient than Midcap. Yet, from the trading frequency statistics of Tables 4.3 and 4.4, we may also deduce that part of this "predictability" is related to non-synchronous trading. The next step is thus to investigate which of the former effects is the main cause of the predictability. The proposed methodology is described below.

The VAR model shown in Section 4.6.2 indicates that the first three and the sixth (one-minute) Nifty lags are significant in determining the value of the Midcap, in case of the high frequency data set. Therefore we look at the Midcap initial returns during the first six minutes of the trading day [denoted $IR(M)_{t+1}$], the Nifty overnight returns [denoted $OR(N)_{t \to t+1}$], and the Midcap overnight returns [denoted $OR(M)_{t \to t+1}$]. If the observed six-minute lead-lag effect consists of non-synchronous trading, we may expect this predictability to persist following the overnight (or weekend) break. This rests on the notion that it takes around six minutes for sufficient transactions to take place in the less liquid stocks, to achieve the required adjustment in respect of overnight news. In this way, if $OR(N)_{t \to t+1}$ is correlated with $IR(M)_{t+1}$, this may be taken as an indication of non-synchronous trading.

Conversely, if the observed predictability consists of inherent inefficiency in terms of traders not following smaller capitalisation stocks as closely, we may expect the lead-lag effect to disappear following the overnight break. Assuming that traders have enough time to process news during such break, the overnight price adjustment in the Midcap index should show up contemporaneously with that of the Nifty. Thus, if $OR(N)_{t \to t+1}$ is correlated with $OR(M)_{t \to t+1}$ (as opposed to $IR(M)_{t+1}$), this may be taken as an indication that the predictability observed during the day consists of inherent inefficiency.

Two approaches are taken in order to test for the correlation as between indices around the overnight breaks. The first test consists of estimating the simple correlation as between the respective series. The sample period consisted of 111 observations ranging from 11th June 1999 to 16th November 1999. These dates were deliberately chosen to obtain a sample period where no initial call auctions were held. The data set featured one missing observation in $IR(M)_{t+1}$ given that the intra-day file for the 22nd September 1999 was unavailable. The latter date was omitted when estimating the correlation coefficients. Results shown in Table 4.8

[30] Similar conclusions that foreign investors contribute more actively to market efficiency were empirically discovered by Tian and Wan (2004) in an investigation of the Chinese and Hong Kong share market.

Panel A, reveal that $OR(N)_{t \to t+1}$ is correlated to a higher degree with $IR(M)_{t+1}$, indicating that the observed predictability constitutes non-synchronous trading effects since the overnight news is still reflected in the Midcap with a six-minute delay.

The second related test involves estimating two OLS regressions, to infer whether $OR(N)_{t \to t+1}$ is more correlated with $OR(M)_{t \to t+1}$ or with $IR(M)_{t+1}$:

$$OR(M)_{t \to t+1} = \alpha + \beta OR(N)_{t \to t+1} + \varepsilon \tag{4.13}$$

$$IR(M)_{t+1} = \alpha + \beta OR(N)_{t \to t+1} + \varepsilon \tag{4.14}$$

where α and β are estimated coefficients, and ε is an error term.

Given the missing intra-day observation in the time series, the sample period was split up, and two separate estimations for each model were undertaken. The results shown in Table 4.8 Panel B, are qualitatively the same across the sub-sample periods. The explanatory statistics and t-ratios again show that the $OR(N)_{t \to t+1}$ is correlated to a higher degree with the $IR(M)_{t+1}$. Overall, both of the above tests point that the predictability as between indices persists around the overnight breaks. This lead-lag relationship may not be reasonably attributed to traders delaying the adjustment of their expectations, since during the overnight period one may assume that participants have ample time to do so.

Thus, the lead-lag relationship from Nifty to Midcap at high-frequency data is more attributable to non-synchronous trading effects. Yet, the lead-lag effect which runs from Midcap to Nifty (which cannot be attributed to non-synchronous trading) implies that part of this predictability effect constitutes an actual lead-lag relationship. Possible economic explanations for such a relationship might be spillover effects amongst stocks, though one cannot rule out the possibility that such an effect is a mere coincidence. These results are in line with the discussion by Atchison, Butler and Simonds (1987) and Lo and MacKinlay (1990) that index or portfolio data tend to exhibit higher autocorrelation than that which may be exclusively expected from non-synchronous trading effects.

The latter investigation thus yields an important contribution as regards the interpretation of predictability. Predictability and Granger-Causality effects do not necessarily imply actual causality. This does not simply reflect the possibility that the analysed time series may be responding to an exogenous variable. Absence of actual causality may also be due to non-synchronous trading which results in less liquid stocks (apparently) taking longer to adjust to new information.

Table 4.8: Correlation as between Indices around Overnight Trading Breaks

Panel A: Correlation Estimations

Correlation between $OR(N)_{t\to t+1}$ and $OR(M)_{t\to t+1}$: 0.2916
Correlation between $OR(N)_{t\to t+1}$ and $IR(M)_{t+1}$: 0.5153

Sample period: 11th June 1999 to 16th November 1999 (112 observations)

Panel B: Regression Estimations

First Model: Dependent Variable is $OR(M)_{t\to t+1}$

Sample Period: # Observations	11-Jun-1999 to 21-Sep-1999 72		23-Sep-1999 to 16-Nov-1999 39	
	Coefficient	T-Ratio	Coefficient	T-Ratio
α	0.00012	(0.96)	0.00003	(0.18)
$OR(N)_{t\to t+1}$	0.75604 ***	(3.33)	0.28411	(1.35)
R-bar-squared	0.1246		0.0213	

Second Model: Dependent Variable is $IR(M)_{t+1}$

Sample Period: # Observations	11-Jun-1999 to 21-Sep-1999 72		23-Sep-1999 to 16-Nov-1999 39	
	Coefficient	T-Ratio	Coefficient	T-Ratio
α	0.00257 ***	(3.39)	0.00213	(0.95)
$OR(N)_{t\to t+1}$	7.5782 ***	(5.69)	9.5373 ***	(3.42)
R-bar-squared	0.3065		0.21964	

The table summarises the results of two different approaches to infer the correlation as between the Nifty and Midcap indices. Statistical significance at the 99% level of confidence is denoted by ***. Panel A shows the results obtained when estimating the simple correlation between series, which indicate that the Overnight Nifty Return [$OR(N)_{t\to t+1}$] is more correlated with the Initial Midcap Return [$IR(M)_{t+1}$], rather than with the Overnight Midcap Return [$OR(M)_{t\to t+1}$].

Panel B shows regression estimations which confirm that $OR(N)_{t\to t+1}$ performs better in explaining $IR(M)_{t+1}$ rather than $OR(M)_{t\to t+1}$ (both in terms of t-ratios, and in terms of R^2). In estimating the models in Panel B, the sample period was split into two due to a missing intra-day observation.

Given that the tests in both panels indicate that $OR(N)_{t\to t+1}$ is more correlated with $IR(M)_{t+1}$, the lead-lag relationship between the Nifty and the Midcap is more attributable to non-synchronous trading, rather than to a delayed adjustment of traders' expectations.

The findings also relate to the issue of market efficiency – in particular, predictability effects in the data do not necessarily imply market inefficiency. Whilst one may attempt to partly predict the Midcap value from the lagged Nifty particularly when using high frequency data, this does not necessarily translate into profitable opportunities. Although the Midcap value might be temporarily mispriced being calculated through stock prices prevailing in past trades, it does not mean that traders are still prepared to transact at such "outdated" prices. In addition, there is also a possibility of observing some transitory transactions at "outdated" prices in an efficient market. This rests on the scenario that following the release of news, some limit orders submitted prior to the release are not cancelled immediately and efficient traders "pick off" these orders. This would result in mispriced transactions – yet it does not mean that the market is inefficient.

4.9 Conclusion

One of the main branches of research in market microstructure relates to the area of market efficiency. Non-synchronous trading effects can give the impression that market participants are adjusting their expected values of stocks following a delay. In this way non-synchronous trading effects may lead to flawed inferences as regards market efficiency. This investigation shows that predictability in stock prices does not necessarily contradict market efficiency. Factors such as non-synchronous trading and market participants "picking off" mispriced orders following the arrival of new information, may give the impression that the traders are not adjusting their expectations immediately. This confirms that the main criterion for an inefficient market is the existence of profitable trading opportunities and not predictability – a notion formerly discussed in various studies including Buckle, Clare and Thomas (1999) and Day and Wang (2002).

This research has investigated the lead-lag effects in NSE stock price data using different methodologies. The main empirical observation is that the Nifty index leads the Midcap index – particularly when considering high frequency data. When analysing trading break returns it was noted that such lead-lag effects persist. In such cases, the predictability cannot be attributed to traders' delayed expectation adjustments, since during an overnight period market participants have sufficient time to adjust their expected values of stocks. Thus we may conclude that lead-lag effects are mainly caused by non-synchronous trading, and that this predictability is not likely to result in abnormal profit opportunities. Yet, in line with previous studies, we may also note that non-synchronous trading is not the exclusive cause of observed predictability. In particular, the feedback effect from Midcap to Nifty may not be attributed to non-synchronous trading given that the former index is composed of less liquid stocks as compared to the latter. Finally, we cannot rule out the possibility that part of the predictability emanates from stock price limits, in the sense that these might delay prices from adjusting to news. Yet, any effects emanating from price limits should not be highly prominent since these are not expected to induce causality in any particular direction, and their magnitude should be small as compared to that of non-synchronous trading.

The main contributions of this investigation to the literature are three-fold. Firstly, it was confirmed that non-synchronous trading effects may be detected through lead-lag effects in stock prices. Previous studies tended to focus on the serial correlation structure or else lead-lag effects were tested for at lower sampling frequencies. Secondly, the investigation proposed a simple methodology constituting of the analysis of trading break and post-trading break returns in order to infer whether predictability is more attributable to non-synchronous trading as opposed to actual delayed price adjustments.

Thirdly, through analysing data sampled at different frequencies, it was formally shown that non-synchronous trading effects tend to become more pronounced in high-frequency data. This explains why previous studies conducted through lower frequency data such as Chiao, Hung and Lee (2004) did not detect any significant causality, and this may be attributed to the tendency for trading intensity to vary throughout the day. The results are also in line with the empirical evidence of Papachristou (1999), who compared daily frequency serial correlation to weekly frequency serial correlation and found that non-synchronous trading effects are more evident in higher frequency data. This implies that researchers aiming to study non-synchronous trading effects stand a better chance of obtaining significant empirical evidence if they use high-frequency data. Conversely, researchers who use high-frequency data in investigating unrelated issues should consider the possibility that their findings may be biased due to non-synchronicity. For instance, non-synchronous trading effects should be taken into consideration when evaluating the adequacy of a given market setup in terms of efficiency.

Another feature of this analysis which is worthy of note, is the application of non-synchronous trading concepts in the context of an emerging market. Non-synchronous trading might be even more relevant to emerging markets, given that such markets are often found to be less liquid.

This investigation also suggests further research issues. Firstly, one potential avenue might lie in the re-interpretation of previous studies. Most of the latter studies were based on daily data. In this way, the likely increases in trading activity at the end of the day probably diminished non-synchronous trading effects, and this might amount to an under-estimation of the effects of non-synchronous trading on stock price data. Another potential research issue lies in the specific investigation of individual stock price high-frequency data. In addition, following the notion that trading activity varies throughout the trading day, one may also inquire how non-synchronous trading effects become more pronounced during the middle of the day when trading activity tends to abate.

Finally, whilst this topic is of significance on its own merits, non-synchronous trading effects are also important in interpreting features relating to NSE volatility – which is the issue tackled in the next empirical chapter.

APPENDIX 4.1

Serial Correlation Statistics For The First Five Lags of Log Nifty, Log Midcap, Log Return Nifty and Log Return Midcap.

Daily Frequency Data				
Order	**Autocorrelation Coefficient**	**T-Ratio**	**Box-Pierce Statistic**	**Ljung-Box Statistic**
Log Nifty				
1	0.991	(35.39)	1235.2	1238.2
2	0.982	(20.04)	2447.4	2454.3
3	0.973	(15.69)	3637.8	3649.4
4	0.965	(13.22)	4807.6	4824.7
5	0.956	(11.52)	5956.9	5980.5
Log Midcap				
1	0.997	(35.61)	1249.5	1252.5
2	0.994	(20.29)	2490.2	2497.2
3	0.990	(15.71)	3722.3	3734.2
4	0.987	(13.34)	4945.7	4963.4
5	0.983	(11.70)	6160.4	6184.9
Log Return Nifty				
1	0.071	(2.54)	6.361	6.376
2	-0.033	(1.18)	7.727	7.747
3	0.003	(0.11)	7.741	7.761
4	0.045	(1.61)	10.258	10.289
5	0.018	(0.64)	10.674	10.708
Log Return Midcap				
1	0.153	(5.46)	29.404	29.475
2	-0.003	(0.10)	29.418	29.488
3	0.035	(1.21)	31.000	31.077
4	0.015	(0.52)	31.266	31.344
5	0.016	(0.55)	31.570	31.649

… continued overleaf

Appendix 4.1 (continued)

One-Minute Frequency Data				
Order	**Autocorrelation Coefficient**	**T-Ratio**	**Box-Pierce Statistic**	**Ljung-Box Statistic**
Log Nifty				
1	0.999	(55.50)	2964.8	2967.8
2	0.998	(31.19)	5924.1	5931.1
3	0.997	(24.32)	8877.6	8889.6
4	0.996	(20.75)	11825.1	11843.1
5	0.995	(18.09)	14766.7	14791.6
Log Midcap				
1	0.999	(55.50)	2967	2970
2	0.999	(31.22)	5929.7	5936.7
3	0.998	(24.34)	8887.7	8899.7
4	0.997	(20.77)	11840.2	11858.2
5	0.996	(18.11)	14786.8	14811.7
Log Return Nifty				
1	0.272	(15.11)	219.470	219.692
2	0.097	(4.85)	247.344	247.603
3	0.052	(2.60)	255.419	255.692
4	0.016	(0.80)	256.179	256.453
5	0.015	(0.75)	256.876	257.152
Log Return Midcap				
1	0.222	(12.33)	145.853	146.000
2	0.093	(4.89)	171.496	171.678
3	0.126	(6.63)	218.941	219.203
4	0.065	(3.25)	231.639	231.926
5	0.039	(1.95)	236.157	236.455

APPENDIX 4.2

Selecting the Order of the VAR for Daily Data

The table below shows the Akaike Information Criterion (AIC), the Schwarz Bayesian Criterion (SBC), the maximised values of the Log-Likelihood Function (LL) and Log-Likelihood Ratio Test Statistics (LR) for a preliminary 24 order VAR which was estimated on the log returns series of Nifty and Midcap. Tests were based on 1232 observations.

Both the Akaike Information Criterion and the Schwarz Bayesian Criterion select a VAR(1) model, yet the log-likelihood ratio statistics reject all orders less than 16. Therefore, both a VAR(1) and a VAR(16) model were estimated, and their diagnostics were compared as shown in Appendix 4.3.

Order	AIC	SBC	LL	LR Test	
24	7011.9	6761.2	7109.9	-	
23	7015.1	6774.7	7109.1	$\chi^2(4)=$	1.5566 [.817]
22	7014.0	6783.8	7104.0	$\chi^2(8)=$	11.8435 [.158]
21	7016.4	6796.4	7102.4	$\chi^2(12)=$	15.1076 [.236]
20	7020.1	6810.4	7102.1	$\chi^2(16)=$	15.5466 [.485]
19	7022.1	6822.5	7100.1	$\chi^2(20)=$	19.6788 [.478]
18	7025.1	6835.8	7099.1	$\chi^2(24)=$	21.6473 [.600]
17	7021.1	6842.1	7091.1	$\chi^2(28)=$	37.5427 [.107]
16	7021.9	6853.0	7087.9	$\chi^2(32)=$	44.0813 [.076]
15	7021.4	6862.8	7083.4	$\chi^2(36)=$	53.0531 [.033]
14	7023.6	6875.2	7081.6	$\chi^2(40)=$	56.7236 [.042]
13	7021.2	6883.0	7075.2	$\chi^2(44)=$	69.5188 [.008]
12	7018.3	6890.4	7068.3	$\chi^2(48)=$	83.3006 [.001]
11	7020.9	6903.2	7066.9	$\chi^2(52)=$	86.1284 [.002]
10	7023.5	6916.1	7065.5	$\chi^2(56)=$	88.8453 [.003]
9	7020.9	6923.7	7058.9	$\chi^2(60)=$	102.078 [.001]
8	7021.6	6934.6	7055.6	$\chi^2(64)=$	108.616 [.000]
7	7023.6	6946.9	7053.6	$\chi^2(68)=$	112.551 [.001]
6	7026.7	6960.2	7052.7	$\chi^2(72)=$	114.421 [.001]
5	7029.0	6972.7	7051.0	$\chi^2(76)=$	117.797 [.002]
4	7032.1	6986.0	7050.1	$\chi^2(80)=$	119.683 [.003]
3	7032.6	6996.8	7046.6	$\chi^2(84)=$	126.572 [.002]
2	7031.7	7006.1	7041.7	$\chi^2(88)=$	136.375 [.001]
1	7033.0	7017.7	7039.0	$\chi^2(92)=$	141.744 [.001]
0	7012.5	7007.4	7014.5	$\chi^2(96)=$	190.817 [.000]

The Log-Likelihood Ratio Statistic (LR), tests the null hypothesis that the order of the VAR is p, against the alternative that it is q, where q is the maximum order of the VAR (in this case, q is equal to 24 as permitted by the software programme). The test is χ^2 distributed with $m^2(q-p)$ degrees of freedom, where m denotes the number of variables in the VAR. The probability of falsely rejecting the null hypothesis is shown in square brackets.

APPENDIX 4.3

Selecting the Order of the VAR for Daily Data

The table shows various explanatory power statistics for the VAR(1) and the VAR(16) models. The VAR(1) model was selected on the basis of higher System Log Likelihood Ratio, higher Log Likelihood Ratios for the individual equations, higher F-statistics, and higher Akaike Information Criterion and Schwarz Bayesian Criterion. Besides, it is not clear on practical grounds why an index shock taking place on day *t*, should still affect the price series on day *t+16*.

VAR (1)	Nifty Regression	Midcap Regression
Equation Log-likelihood	3416	3124.4
F-Statistic F(2,1252)	3.2571	15.1028
R-Bar-Squared	0.0036	0.0220
Akaike Info. Criterion	3413	3121.4
Schwarz Bayesian Criterion	3405.3	3113.7
System Log-likelihood	7168.3	
VAR (16)	**Nifty Regression**	**Midcap Regression**
Equation Log-likelihood	3399.8	3111.7
F-Statistic F(32,1207)	1.3277	2.5443
R-Bar-Squared	0.0084	0.0384
Akaike Info. Criterion	3366.8	3078.7
Schwarz Bayesian Criterion	3282.3	2994.2
System Log-likelihood	7135.8	

APPENDIX 4.4

An Analysis of the Occurrences of Forecast Error Terms for the VAR(1) regressions.

The largest 40 error terms of the VAR(1) regressions were tabulated to inquire whether such errors may be attributed to a particular day of the week. The table shows that the error terms are distributed across the week. (A lower number of Saturday occurrences may be explained by the fact that the exchange is not usually open for trading on this day). If we hypothesise that more volatile returns are realised on Mondays, this would imply that the VAR(1) regressions would perform badly in forecasting the Monday return, as well as the Tuesday returns (given that the Monday information is then used to forecast the Tuesday return). A higher number of Monday and Tuesday return forecast errors is not clearly evident from the table. This is in line with the empirical results of Choudhry (2000) who found that the change in volatility on Mondays was not significant on the Indian market.

	Log Return Nifty Regression	Log Return Midcap Regression
Monday	11	9
Tuesday	6	6
Wednesday	5	8
Thursday	7	5
Friday	9	11
Saturday	2	1
TOTAL	40	40

APPENDIX 4.5

Selecting the Order of the VAR for One-Minute Frequency Data

The table below shows the Akaike Information Criterion (AIC), the Schwarz Bayesian Criterion (SBC), the maximised values of the Log-Likelihood Function (LL) and Log-Likelihood Ratio Test Statistics (LR) for a preliminary 24 order VAR which was estimated on the log returns series of Nifty and Midcap. Tests were based on 2945 observations.

The Akaike Information Criterion selects an order 9 VAR, whilst the Schwarz Bayesian Criterion selects an order 3 VAR. The log-likelihood ratio statistics rejects all orders less than 7, and therefore an order 9 VAR was selected.

Order	AIC	SBC	LL	LR Test	
24	36499.6	36206.2	36597.6	-	
23	36502.7	36221.3	36596.7	$\chi^2(4)$=	1.8854 [.757]
22	36505.2	36235.8	36595.2	$\chi^2(8)$=	4.8352 [.775]
21	36508.3	36250.8	36594.3	$\chi^2(12)$=	6.6465 [.880]
20	36507.2	36261.7	36589.2	$\chi^2(16)$=	16.7996 [.399]
19	36510.6	36277.0	36588.6	$\chi^2(20)$=	18.1479 [.578]
18	36514.3	36292.8	36588.3	$\chi^2(24)$=	18.6322 [.771]
17	36516.6	36307.1	36586.6	$\chi^2(28)$=	22.0035 [.781]
16	36518.9	36321.3	36584.9	$\chi^2(32)$=	25.5161 [.785]
15	36521.5	36335.9	36583.5	$\chi^2(36)$=	28.2575 [.818]
14	36524.9	36351.3	36582.9	$\chi^2(40)$=	29.4061 [.891]
13	36524.7	36363.0	36578.7	$\chi^2(44)$=	37.9461 [.728]
12	36527.0	36377.3	36577.0	$\chi^2(48)$=	41.2341 [.744]
11	36528.0	36390.3	36574.0	$\chi^2(52)$=	47.3077 [.659]
10	36527.9	36402.2	36569.9	$\chi^2(56)$=	55.4008 [.497]
9	36528.2	36414.5	36566.2	$\chi^2(60)$=	62.8028 [.377]
8	36525.6	36423.8	36559.6	$\chi^2(64)$=	76.1749 [.142]
7	36523.8	36434.0	36553.8	$\chi^2(68)$=	87.6988 [.054]
6	36521.6	36443.8	36547.6	$\chi^2(72)$=	100.013 [.016]
5	36511.2	36445.3	36533.2	$\chi^2(76)$=	128.874 [.000]
4	36512.1	36458.2	36530.1	$\chi^2(80)$=	135.176 [.000]
3	36512.9	36471.0	36526.9	$\chi^2(84)$=	141.469 [.000]
2	36489.0	36459.1	36499.0	$\chi^2(88)$=	197.198 [.000]
1	36474.0	36456.1	36480.0	$\chi^2(92)$=	235.207 [.000]
0	36242.7	36236.7	36244.7	$\chi^2(96)$=	705.919 [.000]

The Log-Likelihood Ratio Statistic (LR), tests the null hypothesis that the order of the VAR is p, against the alternative that it is q, where q is the maximum order of the VAR (in this case, q is equal to 24 as permitted by the software programme). The test is χ^2 distributed with $m^2(q-p)$ degrees of freedom, where m denotes the number of variables in the VAR. The probability of falsely rejecting the null hypothesis is shown in square brackets.

APPENDIX 4.6

Orthogonalised and Generalised Impulse Response Functions for Nifty Shocks

	Daily Frequency		One-Minute Frequency	
Horizon	LRN	LRM	LRN	LRM
0	0.0159280000	0.0159800000	0.000571000	0.000196300
1	0.0011321000	0.0022997000	0.000147700	0.000142600
2	0.0000962600	0.0003592000	0.000052970	0.000067450
3	0.0000104100	0.0000580700	0.000032140	0.000063490
4	0.0000013860	0.0000095130	0.000011170	0.000032250
5	0.0000002087	0.0000015660	0.000017350	0.000019250
6	0.0000000333	0.0000002583	-0.000010080	0.000034890
7	0.0000000054	0.0000000426	0.000008881	0.000008155
8	0.0000000009	0.0000000070	-0.000003777	-0.000018410
9	0.0000000001	0.0000000012	-0.000005474	0.000022950
10	0.0000000000	0.0000000002	-0.000003544	0.000007513
11	0.0000000000	0.0000000000	-0.000005020	-0.000000671
12	0.0000000000	0.0000000000	-0.000002600	0.000001181
13	-	-	-0.000005990	-0.000001526
14	-	-	-0.000001089	-0.000001025
15	-	-	-0.000000632	0.000000088
16	-	-	-0.000002573	-0.000001776
17	-	-	-0.000000853	-0.000000826
18	-	-	-0.000001350	-0.000000078
19	-	-	-0.000000700	-0.000000788
20	-	-	-0.000000418	-0.000000539

The IRFs show the effect of a shock of one standard error in Nifty Log Return, on the variables included in the VAR i.e. LRN (Nifty Log Return) and LRM (Midcap Log Return). The Generalised and Orthogonalised IRFs for a Nifty shock are identical, since Nifty is the first variable in the VAR (Pesaran and Shin; 1997). The IRF estimated using daily data is shown for a 12 day horizon, whilst the IRF estimated through one-minute data is shown for a 20 minute horizon.

APPENDIX 4.7

Orthogonalised and Generalised Impulse Response Functions for Midcap Shocks

Panel A: IRFs estimated at daily frequency

	Orthogonalised		Generalised	
Horizon	LRN	LRM	LRN	LRM
0	0.0000000000	0.0121840000	0.0126660000	0.0200950000
1	0.0001654000	0.0020492000	0.0010005000	0.0030712000
2	0.0000373100	0.0003406000	0.0000991700	0.0004922000
3	0.0000067670	0.0000563800	0.0000123800	0.0000803600
4	0.0000011540	0.0000093170	0.0000018020	0.0000132100
5	0.0000001928	0.0000015390	0.0000002829	0.0000021790
6	0.0000000320	0.0000002541	0.0000000458	0.0000003595
7	0.0000000053	0.0000000420	0.0000000075	0.0000000594
8	0.0000000009	0.0000000069	0.0000000012	0.0000000098
9	0.0000000001	0.0000000011	0.0000000002	0.0000000016
10	0.0000000000	0.0000000002	0.0000000000	0.0000000003
11	0.0000000000	0.0000000000	0.0000000000	0.0000000000
12	0.0000000000	0.0000000000	0.0000000000	0.0000000000

The IRFs show the effect of a shock of one standard error in Midcap Log Return, on the variables included in the VAR i.e. LRN (Nifty Log Return) and LRM (Midcap Log Return). Both the Generalised and Orthogonalised IRF versions, for a 12 day horizon are shown.

... continued overleaf

Appendix 4.7 (continued)

Orthogonalised and Generalised Impulse Response Functions for Midcap Shocks

Panel B: IRFs estimated at one-minute frequencies

	Orthogonalised		Generalised	
Horizon	LRN	LRM	LRN	LRM
0	0.000000000	0.000390700	0.000256300	0.000437300
1	0.000063200	0.000010430	0.000122800	0.000073350
2	0.000000448	-0.000015820	0.000024180	0.000016150
3	0.000013900	0.000015880	0.000026850	0.000042690
4	-0.000003950	0.000005917	0.000001487	0.000019770
5	0.000011270	-0.000004384	0.000017860	0.000004724
6	-0.000007349	0.000016920	-0.000011090	0.000030780
7	-0.000032240	-0.000013800	-0.000024820	-0.000008669
8	-0.000006968	0.000004473	-0.000007922	-0.000004266
9	-0.000012130	0.000000515	-0.000013300	0.000010760
10	-0.000003888	-0.000005109	-0.000005065	-0.000001192
11	-0.000000872	-0.000003480	-0.000003033	-0.000003411
12	-0.000001323	-0.000000169	-0.000002349	0.000000379
13	-0.000000823	-0.000004060	-0.000003425	-0.000004313
14	-0.000001035	0.000000584	-0.000001414	0.000000061
15	-0.000001083	0.000000095	-0.000001251	0.000000125
16	-0.000000937	-0.000001974	-0.000001992	-0.000002561
17	-0.000000326	-0.000000059	-0.000000674	-0.000000424
18	-0.000000094	-0.000000471	-0.000000690	-0.000000456
19	0.000000029	-0.000000693	-0.000000289	-0.000000973
20	0.000000352	0.000000095	0.000000126	-0.000000157

The IRFs show the effect of a shock of one standard error in Midcap Log Return, on the variables included in the VAR i.e. LRN (Nifty Log Return) and LRM (Midcap Log Return). Both the Orthogonalised and Generalised versions of the Functions are shown, for a 20-minute horizon.

CHAPTER 5:

THE SEASONALITY OF STOCK PRICE VOLATILITY AND ITS CONNECTION WITH EXCESSIVE PRICE MOVEMENTS

5.1 Introduction

Empirical analyses of the volatility of financial assets have exposed various "stylised facts", such as weekly and monthly seasonality and volatility clustering. Volatility is directly related to returns and to risks, and one important research question is whether markets are excessively volatile. The latter issue is central to the market microstructure field, since it translates into whether asset prices exclusively reflect the underlying information, or whether they are additionally subject to other factors which are likely to emanate from the market setup and traders' behaviour.

The main aim of this chapter is to model NSE volatility and to inquire whether the observed volatility is justified or excessive. A whole body of literature and tests have tackled this issue. Studies such as Shiller (1981) inferred whether volatility is excessive or otherwise by comparing stock price changes to information about expected dividends, since theoretically prices should be equal to the present value of expected future dividends. This approach cannot be adapted to index data in a straightforward way for a variety of reasons. Firstly stock indices do not directly yield dividends. Secondly, when tackling the topic from a market microstructure point of view, there are potential advantages to be reaped from using high frequency data – yet dividend data are inherently low frequency. Therefore alternative methodologies are used in this study.

The main research question of whether NSE volatility is justified or excessive is split up into two subsidiary questions. The first one is whether the degree of volatility is related to information flow. Previous studies on Monday effects and monthly seasonality as described in Section 5.2, are used to infer expected information flow patterns on NSE, and it is then inquired whether volatility rises during those periods when new information becomes available. Increased volatility during the latter periods is likely to be the response to new information, and therefore it is more likely to be justified.

The second related question concerns the relationship between volatility and returns. In particular, if we consider volatility as a measure of risk, then finance theory would suggest that this should be positively related to returns. This question is investigated through GARCH-in-Mean models.

Thus, this empirical analysis is not merely aimed at estimating econometric models, but the latter serve as a basis for discussing whether NSE volatility may be deemed justified, or whether it appears excessive as often witnessed in emerging financial markets. The detection (and possibly the reduction) of unjustified volatility is a central objective of market microstructure researchers and practitioners. This analysis is therefore relevant to both of the latter, since it pinpoints excessive volatility features on NSE.

The scope of this chapter is not limited to any one particular type of volatility; indeed different technical definitions of the term "volatility" are adopted, including realised volatility, process volatility, conditional and unconditional volatility. An additional strength of the analysis is that models are estimated by using data of different frequencies depending on the issue being investigated; indeed one-minute frequency data, daily data and monthly data are all used in the analysis. Whilst the study does not propose new econometric methodology, one main innovation lies in the interpretation of different models. In particular, the possible inter-relationships between these models might not have been sufficiently emphasised in previous literature. In addition the study explores how different empirical tests may be used to make inferences on whether volatility is justified or excessive, in the absence of data about dividend expectations.

The analysis starts with a research background in Section 5.2, whilst an overview of the main methodologies and a note on possible findings of the study are shown in Section 5.3. After a descriptive note on the data in Section 5.4, the empirical models relating to volatility are estimated. Section 5.5 considers the differences in opening volatility across different days of the week, Section 5.6 focuses on the monthly seasonality of volatility and Section 5.7 investigates the relationship between volatility and returns. Results are jointly discussed in Section 5.8 where an answer to the main research question about the justification of volatility is proposed. Section 5.9 concludes.

5.2 Review of Relevant Literature

Finance literature has proposed different measures of volatility. According to Dacorogna *et. al.* (2001) we may broadly classify such measures into three categories as follows. Realised volatility is calculated from past data and includes measures such as the standard deviation of a price series over a particular time period. Other econometric models consider volatility as a process, as in the case of a GARCH model. Implied volatility is inferred through the theoretical relationship between options prices and the prices of the underlying instruments.

In addition, we may also distinguish between conditional and unconditional volatility. Whilst unconditional volatility statistics such as the variance are calculated through a whole sample of data, conditional volatility only depends on *past* data, rather than the whole data set. For instance, in a GARCH model, the conditional volatility of day t depends on shocks and the conditional volatility of previous days.

One important inference to be gained from this study is whether NSE Index volatility may be deemed justified or excessive. This is inferred by comparing NSE volatility patterns to the "stylized facts" of volatility prevailing on other markets. As found in the existing literature, such volatility patterns may be information-related. Thus, if NSE volatility escalates during periods where new information is expected to be higher, volatility is (partly) justified. In this way this literature survey includes a description of the main volatility patterns found in previous research, and their possible connections with information flow. Section 5.2.1 relates to intra-day volatility whilst Section 5.2.2 discusses inter-day volatility.

5.2.1 Intra-Day Volatility

Empirical research tends to converge towards the same conclusions regarding volatility variations during the trading day, but the explanation for such findings is not fully resolved.

Wood, McInish and Ord (1985) examined one minute interval returns for transaction data spanning over six months and found several well-defined patterns. During the opening and the closing of the market, returns and standard deviations tend to be higher. The authors argued that there are different distributions for overnight returns, opening returns, end-of day returns and intraday returns, where only the latter is a normal one. Higher returns were realised during the first thirty minutes of trading and at the market close. These differences tend to become less pronounced when one excludes overnight returns. The standard deviations of returns tend to be U-shaped across the day, being thicker in the initial period. This indicates higher levels of activity within these periods. Such patterns cast doubts on the models of stock prices showing i.i.d. increments. Similar findings on U-shaped (or reverse-J-shaped) volatility patterns were presented by Harris (1986), Foster and Viswanathan (1993), Stoll and Whaley (1990) and Abhyankar, *et. al.* (1997).

A W-shaped volatility pattern, which may be explained by a midday trading break, was reported by Andersen, Bollerslev and Cai (2000) who examined 5-minute interval returns for the Nikkei-225 index. Similarly, Bildik (2001) who examined intra-day data for the Istanbul Stock Exchange-100 Index found that returns tend to follow a W-shaped pattern (due to a trading break) whilst volatility tends to follow an L-shaped pattern in both the morning and afternoon trading sessions. The author also noted that higher closing returns may be the result of fund managers "window dressing" their portfolios, in that they bid high prices and accept high ask prices at the end of the day to raise the value of their portfolios.

Shastri, Shastri and Sirodom (1995) analysed opening and closing prices for shares trading on the Stock Exchange of Thailand and found that opening return volatility is around 37% higher than the closing return volatility. Mutjaba Mian and Adam (2001) attributed the initial high volatility on the Australian Stock Exchange to the way in which the opening call auction is structured, whereby it takes around ten minutes for all stocks to trade in the auction. In this way, the initial overnight "news" are not priced in immediately with the first index observation, but rather after the first ten minutes.

Authors such as Clark (1973) and Epps and Epps (1976) argued that heteroskedastic price changes (and trading volumes) are related to differences in information arrival rates. This concept is known as the Mixture of Distribution Hypothesis. Similarly Kalev, *et. al.* (2004) attributed the heteroskedasticity of intra-day returns on the Australian Stock Exchange to time-dependence in the news-arrival process and they noted a reduction in volatility persistence as obtained through a GARCH (1,1) model when they accounted for a news variable such as public company announcements.

Contradictory evidence was obtained by Andersen, Bollerslev and Cai (2000) who used flexible Fourier form regression and found that macroeconomic news announcements were statistically insignificant in explaining intra-day volatility on the Tokyo Stock Exchange. Stoll and Whaley (1990) did not attribute the high initial volatility on NYSE to the release of public information, but to informed trades or non-synchronous trading.

Related conclusions by Miller (1989) and Brock and Kleidon (1992) attributed the higher returns at the NYSE opening and at the closing to the specialists' behaviour of maintaining continuous prices whilst maximising profits. Given that a large number of orders are submitted at the closing and prior to the opening, it may be in the specialist's interests to increase profit margins (spreads) during these periods. Gerety and Mulherin (1992) used NYSE data for the period 1933-1938 and suggested that the high volumes and resulting volatility at the end of the day may be attributed to traders who need to transact prior to the closing. Thus, the former studies do not attribute intra-day volatility patterns to information flow.

Various theoretical models were proposed to explain the differences in intra-day volatility. According to Admati and Pfleiderer (1988) daily volume patterns may be partly explained by traders choosing to transact in the "lowest-cost period" during the day. The resulting variations in liquidity affect the expected returns and therefore volatility as outlined in the empirical study of Coppejans, Domowitz and Madhavan (2001). Yet, while the theoretical model of Admati and Pfleiderer (1988) explains the volume clustering patterns, it does not account for the fact that clustering tends to occur at the beginning and closing of trading days.

Madhavan, Richardson and Roomans (1997) investigated intra-day volatility variations through information patterns and market microstructure features. The authors developed a theoretical model to explain stock price changes and tested it through data for NYSE stocks. They attributed intraday volatility of stock prices both to market microstructure effects and to information. Microstructure effects include trading frictions and price discreteness. Information-related factors include information asymmetry and information flows which consist of public announcements and information garnered from order flow. Whilst new public announcements may cause revisions in traders' beliefs even in the absence of trading activity, the information which may be gained from order flow (by definition) requires trading activity to affect traders' expectations.

In the model of Madhavan, Richardson and Roomans (1997), both public announcements and information gathered from order flow are important causes of volatility, yet the importance of public announcements abates during the day, maybe because companies tend to announce news in the mornings. The reduction in information asymmetry and uncertainty as to the fundamental value of the security during the day, contributes towards a reduction in volatility and spreads. Overall, information-related patterns tend to reduce volatility during the trading day.

The authors also considered various market microstructure effects and found that factors such as rounding of prices tend to be insignificant sources of volatility. A higher portion of volatility is accounted for by the bid-ask bounce and this effect becomes more pronounced during the trading day. Trading costs (as measured through the possibility of executing orders within the bid-ask spread) tend to increase during the day and this eventually leads to pronounced volatility. One possible factor that contributes to increased trading costs is that intermediaries face the risk of accumulating unwanted inventory, which increases their overnight exposure. The interaction between the microstructure effects is also important in explaining volatility.

Thus, according to Madhavan, Richardson and Roomans (1997), information-related volatility tends to decrease during the day, whilst the volatility relating to market microstructure factors gets more pronounced. These effects result in the typical volatility U-shape.

5.2.2 Daily and Monthly Volatility

Various empirical studies concluded that volatility tends to differ across days of the week. Such evidence extends to emerging markets as well. For instance, Bildik (2001) noted that the opening volatility on the Istanbul Stock Exchange on Mondays and Thursdays was higher than the opening volatility on the other days. Whilst he attributed the Monday effect to a higher amount of accumulated information during the non-trading days, he attributed the Thursday effect to the settlement system. In particular, given the presence of a T+2 settlement system, "Thursday buyers" do not have to settle their transactions until after the weekend, gaining two days free interest. Similar notions on the relevance of the settlement system to inter-day effects were presented by Clare, Ibrahim and Thomas (1998) in the context of the Kuala Lampur Stock Exchange.

Researchers have pursued various avenues in explaining inter-day seasonality. French (1980) noted that US stock market Monday returns tended to be predominantly negative, and he outlined the possibility that firms postpone the release of adverse information till after the closing of the exchange on Friday. Yet, the empirical evidence of negative Monday returns tends to be mixed and authors such as Connolly (1989) and Keef and Roush (2005) provided contrasting results. In addition, according to Janssen (2004) who studied US general economic news release patterns during the period 1994-1998, found a lower tendency for the release of economic news during the weekend. Thus, the release pattern of economic news may "dampen" the volatility pattern emanating from any tendencies of companies to release (negative) news during the weekend. Despite this, Janssen (2004) still reported higher Monday volatility for US-related stocks, bonds, treasury bills and the foreign currency market.

Empirical evidence on day-of-the-week effects in volatility has also been documented in the context of the Indian market. Choudhry (2000) studied returns data for seven Asian markets and found that the Indian market was the only one where the change in volatility on Mondays was not significant. The Indian index which was used in this study was the BSE 100, and therefore we cannot rule out the possibility of obtaining different results in this study since a different index is being used. Bhattacharya, Sarkar and Mukhopadhyay (2003) found that day-of-the-week effects for the BSE 100 Index also occurred on a fortnightly basis. They attributed this both to stock exchange regulations, and to the fact that Indian banks report their cash positions to the Reserve Bank of India every other week.

Various authors have proposed explanations for inter-day volatility patterns. Foster and Viswanathan (1990) constructed a theoretical model which explained day-of-the-week effects through informed trading and the release of public information. This model allows for trading volume, variance and trading costs to differ across the week, yet the degree to which these differences are pronounced is dependent on the quality of public information. In particular, those firms with high reporting standards are more likely to witness higher volatility on Mondays. The main cause of inter-day variations in this model is that informed traders' level of private information varies during the week, and it tends to be higher following non-trading periods such as the market opening, particularly on Mondays. During these periods, liquidity traders do not have access to trading prices which are an important source of information and this places informed traders at a privileged position.

In the theoretical model of Admati and Pfleiderer (1989) informed and liquidity traders transact through market makers. The latter have an incentive to create "trading patterns" in that this may restrict informed traders from transacting immediately. If the informed traders transact at a later stage, their private information would have depreciated and this limits the losses of the market makers to informed trades. This process results in patterns in volume, liquidity and volatility and may explain both inter-day and intra-day patterns. Despite this, Lee, Fok, and Liu (2001) suggested that since such trading patterns feature in a cross-section of markets, it is unlikely that the underlying cause is the trading mechanism given that the latter differs across markets.

Other authors have attributed inter-day patterns on financial markets to psychological factors. For instance, authors such as Wilson and Jones (1993) studied various US stock indices and found evidence that post trading-holiday returns are usually higher. Fabozzi, Ma and Briley (1994) associated higher post trading-holiday returns on US futures markets with the notion that people usually feel better after a holiday.

Madureira and Leal (2001) studied Brazilian stock market data, and found that whilst the Monday effect is present in the index, it does not show up when considering the individual stocks. They suggested that Monday effects in index data may be the result of unsuitable index construction, such as the inclusion of less liquid stocks. The authors thus suggested that Monday effects should be confirmed by analysing individual stock data.

Researchers have also focused on monthly effects in stock market data. One issue attracting much attention is the January effect, where it is often observed that higher returns may be earned during this month. Researchers suggested diverse explanations for this effect. For instance Ogden (1990) and Booth, Kallunki, and Martikainen (2001) argued that the January effect may be explained by seasonal liquidity and cash flow factors. Kramer (1994) attributed the effect to risk seasonality, yet Clare, Psaradakis and Thomas (1995) presented contrasting evidence when analysing UK stock market data. Tax-related reasons were considered by Branch (1977) and Dyl (1977) who suggested that investors sell stocks on which they can realise losses at the end of the fiscal year. This depresses stock prices in December, which then recuperate in January. The study of Nassir and Mohammad (1987) in the context of the Malaysian stock market suggests that tax-loss selling cannot on its own explain the January seasonal, since the authors still found a January effect in the absence of a capital gains tax setup.

The portfolio rebalancing actions of fund managers at the end of the year have also been proposed as explanations for the January effect in the studies of Haugen and Lakonishok (1988) and Clare, Psaradakis and Thomas (1995). Yet, according to Sias and Starks (1997) who analysed NYSE-listed stocks, the tax-loss selling hypothesis is a better explanatory factor of the January effect, as compared to window-dressing actions of fund managers. Authors such as Chien, Lee and Wang (2002) suggested that higher January volatility may be due to the fact that the fiscal years of most companies end in December, and earnings are announced in January.

As outlined by Tang (1998), whilst empirical studies on monthly seasonality of returns are numerous, investigations of the monthly seasonality of higher moments of returns are not as common. Tang (1998) found mixed evidence regarding monthly seasonality in higher moments of the Hong Kong Index and other sectoral indices.

One notable feature of financial return data (especially lower frequency data) is asymmetric volatility, in that high volatility is more likely to follow negative returns rather than positive ones. This characteristic has been documented by various researchers including Black (1976). Black's explanation for the asymmetric volatility witnessed in inter-day returns was that a negative return, leads to a decrease in the value of the firm and therefore an increase in the leverage ratio. A higher leverage ratio typically leads to higher volatility of the return on equity ratio. An alternative explanation, as outlined for instance by Siourounis (2002), might be that smaller investors tend to be more risk-averse, and therefore they sell their holdings following price drops in order to stop their losses.

The empirical evidence regarding asymmetric volatility seems to be sensitive to the data frequency. For instance, Mutjaba Mian and Adam (2001) in an empirical study of the Australian Stock Exchange Index found that at higher frequencies such as two hour intervals, the asymmetric response of volatility tends to disappear. The authors argued that one possible reason is that in high frequency data, the asymmetric shocks become disguised amongst a higher level of noise. Lin and Yang (2003) used high frequency data for 12 stocks trading on the Australian Stock Exchange and found that when accounting for buy or sell imbalances, the asymmetric effects in intraday returns may be better predicted.

5.3 Methodology and Possible Results

In addressing the question of whether NSE volatility is justified or otherwise, this empirical study employs different volatility definitions and rigorous measures of volatility, including models estimated through high frequency data. For instance, measures such as return standard deviations, squared returns, scaled intra-day price difference, and the modulus of returns address the notions of "realised volatility" and "unconditional volatility". Conversely, the estimations of EGARCH and EGARCH-M Models focus on "process volatility" and "conditional volatility". The study does not tackle the notion of "implied volatility" mainly since NSE derivatives activity was still in its infancy during the period of interest, which means that historical derivatives data was largely non-existent.

Despite this, one should note that the above distinctions between different volatility measures may be considered of secondary importance, since the main aim is to distinguish between justified and excessive volatility. The adoption of a variety of volatility measures is therefore resorted to with this latter aim in mind. The econometric approaches adopted in this study are outlined in Sections 5.3.1 and 5.3.2, whilst possible results are discussed in Section 5.3.3.

5.3.1 Modelling Seasonality through Dummy Variables

Daily and monthly seasonality of stock prices has often been modelled through dummy variables; for instance four dummy variables may be used to model day-of-the-week effects, whilst eleven dummy variables may be used to model monthly seasonality.

This approach to modelling seasonality – particularly monthly seasonality – was called into question by various authors. For instance Chien, Lee and Wang (2002) noted that one main shortcoming is that OLS regressions assume the absence of heteroskedasticity of returns, which goes against the empirically observed "stylised facts" of stock market data. This may lead to flawed test statistics that are biased towards rejecting the null hypothesis of no seasonality in returns. Nonetheless, this limitation should not be of concern for our purposes due to a number of reasons. Firstly, this research also employs the Kruskal-Wallis test as an alternative non-parametric methodology in order to avoid relying on one criterion. In addition, authors such as Kunkel, Compton and Beyer (2003), noted that this limitation may be addressed by using a large data sample (such as the one at hand).

5.3.2 GARCH Modelling

The ARCH (1) model was developed by Engle (1982). In such a setup, the conditional variance of the error term of the return generating process is regressed on a constant and a lag of the squared error term. One limitation of this approach is that simple ARCH models may require a large number of lags to capture the inherent features of financial data. The GARCH (1,1) model was developed by Bollerslev (1986) and Taylor (1986) and overcomes some of the limitations of the ARCH (1) process. In particular, a GARCH (1,1) process regresses the conditional variance on a constant, a lag of the squared error term and a lag of the conditional variance itself. For instance, returns (r_t) are modelled as an AR(1) process as follows:

$$r_t = \varphi + \rho r_{t-1} + \varepsilon_t \qquad (5.1)$$

The conditional variance of the error term (h_t) is defined as:

$$h_t = \mathrm{var}(\varepsilon_t | \Omega) \qquad (5.2)$$

where Ω is the information set consisting of current and past observations of r_t. The conditional variance is modelled as follows:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (5.3)$$

where ε_t^2 is the squared unexpected return observed during period t.

The required conditions to ensure a non-negative conditional variance are $|\beta_1| < 1$, and $(\alpha_1 + \beta_1) < 1$. It is commonly assumed that the intercept is greater than zero as well. The coefficients α_1 and β_1 represent how volatility is affected by past unexpected returns and the lagged conditional variance.

According to Franses and Van Dijk (2000; pp.138) ARCH models are able to replicate the typical characteristics of financial data including peak-shaped distributions and heteroskedasticity. Numerous studies have employed a GARCH (1,1) approach in modelling stock returns. These include Bollerslev (1987), Poon and Taylor (1992), and Chelley-Steeley and Steeley (1995). GARCH modelling is also relevant to high-frequency data. As the sampling interval gets shorter, it is expected that the coefficients $\alpha_1+\beta_1$ converge to 1.

When estimating GARCH models, a researcher has to decide whether to assume that the standardized errors follow a normal distribution or a Student-t distribution as suggested by Bollerslev (1987). One practical solution to this problem is to estimate a separate model under both assumptions and deciding on the "best fit" model through a relevant criterion such as the Akaike Information Criterion or the Schwarz Bayesian Criterion.

Various extensions and modifications of the GARCH process have been proposed. This is due to the fact that financial time series are often characterised by non-linearity, and this makes the traditional linear GARCH processes sub-optimal for modelling such series. In this way, GARCH literature has been supplemented by more elaborate models which allow for asymmetric volatility characteristics and regime switching. One particular example is the GJR model proposed by Glosten, Jagannathan, and Runkle (1993). In the GJR model, both the sign and the size of the lagged residuals determine the conditional variance.

Exponential GARCH (EGARCH) processes as proposed by Nelson (1991), model the log of the conditional variance and the asymmetric volatility effect partly emerges from the asymmetric shape of the exponential curve. GARCH-in Mean (GARCH-M) models investigate the relationship between stock market volatility and the returns generated by the market, following the notion that risk-averse investors expect higher returns to compensate for a higher volatility risk. The latter two models are discussed in more detail in Section 5.6.

Finally, reference should be made to the limitations of GARCH methodology. Various authors such as Hansen (1994) presented evidence that higher order moments of the error term do not follow a Markov process, i.e. they depend on past values. The former GARCH models do not account for such dependence.

In addition, volatility is likely to be influenced by other factors which might be unaccounted for in the GARCH process. For instance, the volatility of options prices is likely to be influenced by the volatility of the underlying instruments and therefore it might be desirable to account for both factors in a single model. Such a limitation may be addressed by specifying Multivariate GARCH models and GARCHX models (Hwang and Satchell; 2005).

Similarly, the standard GARCH process does not model a direct relationship between volatility and expected returns, as postulated by the Capital Asset Pricing Model. This relationship is directly addressed through GARCH-M processes.

5.3.3 A Note on Possible Findings of this Study

In this Chapter, I seek to describe volatility patterns on NSE and to draw inferences on whether the observed volatility is justified or excessive. Given that the standard methodology for answering the latter question requires data about expected dividends, such approach cannot be readily applied in the context of a stock index since indices do not directly yield dividends. In addition dividend data are inherently low frequency, and therefore of limited relevance when analysing intra-day effects. In this way the research question is split into two subsidiary ones. The first question is whether the observed volatility is related to information flow and the second one is whether volatility is related to returns. If the empirical findings disclose that volatility is connected with information patterns and with returns, then this would imply that NSE volatility is (at least partly) justified. These research questions are addressed through the econometric modelling of data sampled at different frequencies. The empirical research of this Chapter consists of three main investigations as detailed hereunder.

The first investigation considers the opening volatility during different days of the week. A higher opening volatility on Monday would provide evidence that markets are adjusting to news accumulated over the weekend, suggesting a connection between volatility and information flows.

The second analysis considers monthly volatility. One main problem with most of the existing research on monthly volatility and the January effect is that the underlying cause of these effects has not been resolved with certainty. Various possible causes for this effect have been proposed and these include the end of financial years for listed companies or investors' personal decisions regarding tax-loss selling during the month of December. NSE provides an ideal research setting for investigating this issue given that the Indian fiscal year ends in March and in case of most NSE listed companies the financial year ends in March as well. Therefore, higher volatility around the month of March would again provide evidence that volatility is related to information flow. If on the other hand a January effect is noted on NSE, this would be an indication that this effect observed on other markets is not mainly caused by the end of fiscal year or the end of financial year of companies. One cannot rule out the possibility of detecting both a January effect as well as seasonality around the end of the fiscal year – in line with Clare, Psaradakis and Thomas (1995) in the context of the UK equity markets where the fiscal year ends in April.

The third investigation is whether volatility is related to returns. The connection between volatility and returns may be interpreted as a risk-return relationship. A positive relationship between volatility and returns may be expected, following the notion that investors are risk-averse. Such relationship might not necessarily imply that volatility is justified, but at least we may conclude that volatility is being compensated for by a higher return. Absence of a positive volatility-returns relationship indicates that risk on NSE is not related to returns – and therefore this would hint at excessive volatility. The relationship between volatility and returns is analysed through EGARCH-M models. However, such a relationship may only hold over a relatively long period of time. This is due to the fact that over the short-term, stock prices may deviate from their fundamental values. In addition, if higher volatility unfailing yields higher short-term returns, then it would always be advantageous to hold high volatility stocks! Given that a longer data range may be required to capture the volatility-returns relationship, a five year daily time-series is used to estimate EGARCH-M models.

Whilst the above methodologies (particularly the first two) were not meant as investigations to assess whether volatility is justified or otherwise, one may still glean inferences, especially if the results point in the same direction. For instance if it is noted that volatility escalates as more news are released and that it is connected to longer-term returns, then we may infer that volatility is partly justified. If the results disclose that volatility is not related to the typical information flow and to longer-term returns, then this would indicate that part of the volatility is excessive.

5.4 Data and Notation

5.4.1 Intra-Day Data

The original set included high frequency Nifty Index observations for thirty-two trading days, starting at 18th May 1999 and ending on 30th June 1999. In order to avoid any market microstructure bias, the trading days were selected from two different NSE systems. In the first regime the trading day opened and closed through a call auction system with continuous trading held in between. The second regime simply consisted of one continuous trading session.

This empirical study does not focus on the differences between these regimes – these are investigated in Chapters 6 and 7. The trading days were labelled as the "Before" call auction suspension period and the "After" call auction suspension period. This distinction is unnecessary at this stage, but it becomes relevant in subsequent studies and therefore I distinguish between regimes when labelling the trading days for the sake of uniformity.

Two trading days were discarded due to trading halts.[31] The final sample thus consisted of fifteen trading days in each regime as shown in Appendix 5.1. The sample includes a comprehensive cross-section of different days of the week. This minimizes the potential for bias arising from day-of-the-week effects, and is also essential for investigating volatility differences on particular days (Section 5.5).

In sampling the data, the first observation for each particular minute was taken. The observations typically started at 10:00 and ended at 15:29 yielding a total of 330 observations at one minute intervals. This was the case with most of the sessions in the "After" period. In case of the "Before" period, more observations were available owing to the additional call auction trading. During the call auction regime, the observations started at around 09:55 and ended at 15:29. Following this, a closing call auction was held yielding (around) five further observations from 15:50 to 15:55. This resulted in a gap where no observations were available. Given that the returns following this trading gap were typically in the range of the other one-minute interval returns, this period is treated as a regular one-minute interval for modelling purposes. The largest intra-day sample employed in this study consisted of 343 observations at one minute intervals.

In most cases the first observation for the particular minute took place exactly at the start of that particular minute. Yet occasionally the first observation for the minute occurred after one, two or three seconds. Whilst this was not typically coupled with any outliers, one still cannot claim that the sample was taken at uniform intervals. In a sense, this problem is related to the non-synchronous trading of individual stocks as analysed in Chapter 4.

[31] The discarded intra-day data sets were 21st May 1999 and 28th June 1999.

The distributions of logarithmic returns are typically characterised by fat tails, and this implies that extreme observations occur relatively frequently. While eliminating the occasional large return might be desirable for the purpose of fitting a statistical model to the data, it does not always make sense on economic grounds. Indeed, Cont (1999) argued that such large fluctuations may account for a substantial part of the return generated over a particular period, and therefore they deserve attention on part of analysts. No extreme observations were eliminated in this study.

Finally, one should note that the selection of 30 particular trading days leaves the possibility that the conclusions inferred from this study may have been peculiar to the chosen period, and this is an inherent limitation in the research.

5.4.2 Inter-Day Data

The daily data set shows the Nifty Closing observations from 1st January 1999 till 31st December 2003 and includes 1257 observations. A note about the use of index data is warranted. Such methodology has the inherent advantage that the observations are not biased by any peculiar effects taking place within individual stocks. Yet, when keeping in mind that the index value is an average of the prices of the underlying stocks, one may intuitively assume that if the underlying stocks feature non-synchronous trading effects, then these might be present in the index observations as well. Further details about the data set and the Nifty index were included in Chapter 3.

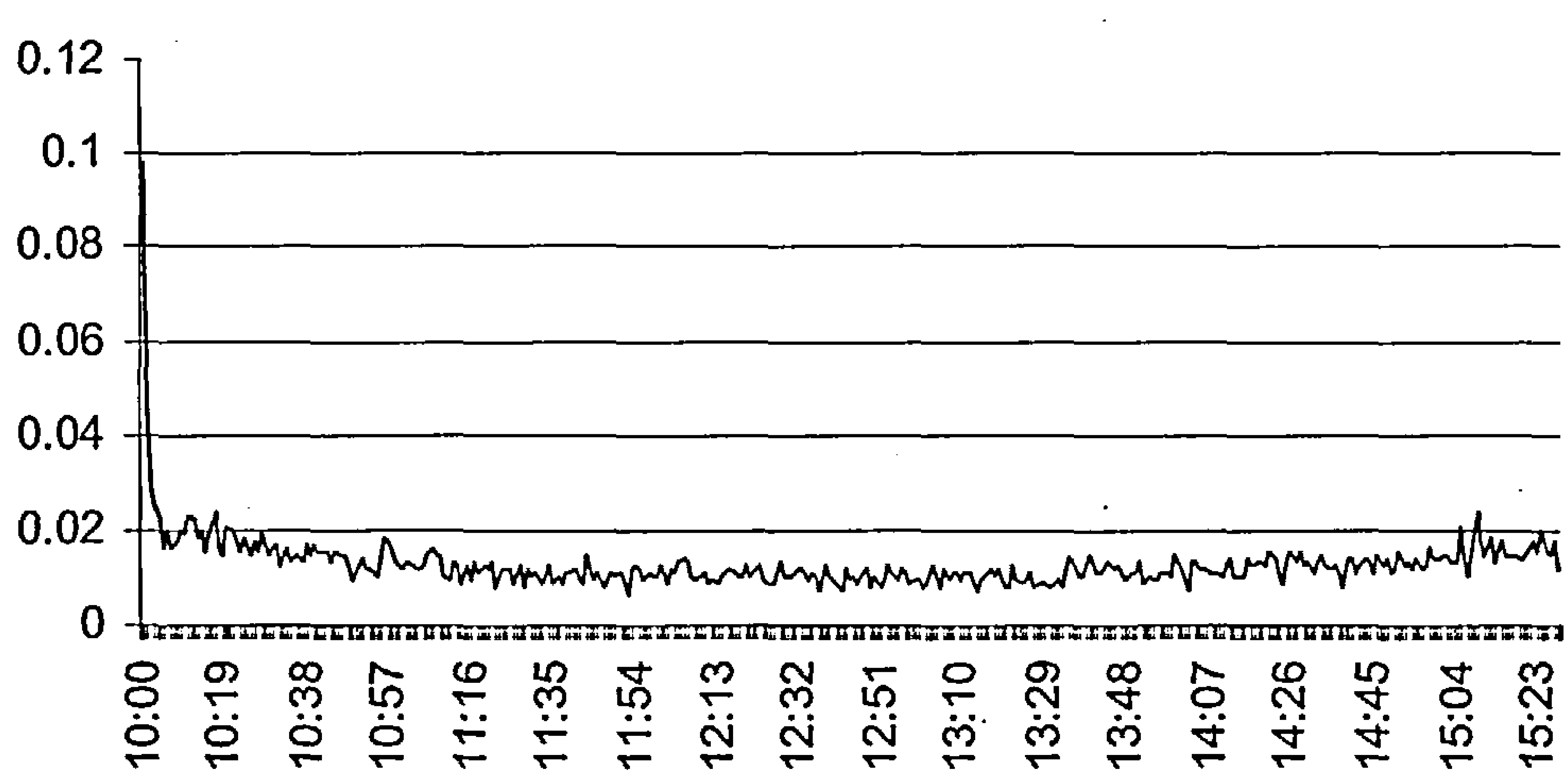
5.5 Intra-Day Volatility and Day-of-the-Week Effects

We now turn to the modelling of intra-day volatility – particularly the opening volatility. The main aim of the analysis is to infer whether volatility is affected by the information flow pattern, following the notion that more news is expected to accumulate during weekend non-trading days, resulting in higher Monday volatility.

5.5.1 Analysing the Intra-Day Data Sets

The analysis started by aggregating the intra-day log return moduli at one-minute intervals, across the sample of 30 trading days. The return plot is shown in Figure 5.1 and is broadly in line with the empirical evidence cited in Section 5.2.1, regarding higher volatility at the opening and at the closing of the trading day.

Figure 5.1: Modulus of Intra-Day Returns



Descriptive statistics for the intra-day distributions are shown in Table 5.1. The absolute value of one-minute log returns ranges from 0.001 to 0.019, whilst the standard deviation of the distributions ranges from 0.0004 to 0.0013. Whilst there is no clear-cut tendency towards skewness in any one direction, positive skewness is more evident than negative skewness. The average of the skewness modulus is 2.02. All the distributions are leptokurtic; the average excess kurtosis is 21.96, which comprises a range of excess kurtosis values from 0.37 to 136.43. Jarque-Bera tests rejected the null hypothesis of a normal distribution at the 99% confidence level for all trading days except A13, where the null hypothesis of normality could not be rejected. The former features are in line with prior research such as Oldfield and Rogalski (1980) who found that as the data frequency increases, the departures from normality become more pronounced. This feature may be due to the fact that returns measured at lower frequencies are a summation of various other shorter-term returns, and therefore they are expected to converge more closely towards the normal distribution following the central limit theorem.

In order to ascertain that the log-returns series are not integrated processes, unit-root tests were conducted (Table 5.2). The null hypothesis of a unit root was rejected for all data sets.

Table 5.1: Descriptive Statistics for One-Minute Interval Log Returns during the Sampled Trading Days

Day	Mean	Std. Devn.	Maximum	Minimum	Coeff. Of Variation	Skewness	Kurtosis-3	Jarque-Bera
				Before Call Auction Suspension				
B 1	0.0000	0.0007	0.0038	-0.0023	34.0100	0.4344	2.1556	76.5
B 2	0.0001	0.0007	0.0055	-0.0019	13.5017	1.5046	11.1520	1,884.6
B 3	0.0000	0.0007	0.0026	-0.0022	22.3177	0.0769	0.9608	13.4
B 4	0.0000	0.0007	0.0031	-0.0028	53.5323	-0.1062	1.8199	47.3
B 5	0.0000	0.0005	0.0013	-0.0025	22.7986	-0.3048	1.6518	43.9
B 6	-0.0001	0.0009	0.0030	-0.0028	14.2107	-0.1832	1.0175	16.4
B 7	-0.0001	0.0008	0.0015	-0.0059	7.2531	-2.8826	14.3103	3,372.0
B 8	0.0000	0.0010	0.0033	-0.0040	36.6011	-0.2491	1.1410	21.8
B 9	0.0001	0.0010	0.0122	-0.0051	7.5165	4.4930	59.0561	50,403.2
B10	0.0000	0.0008	0.0022	-0.0039	35.8040	-0.7191	2.9998	156.3
B11	0.0000	0.0005	0.0015	-0.0031	134.8700	-0.6735	5.0356	382.7
B12	0.0000	0.0005	0.0025	-0.0015	16.7890	0.6833	3.2779	177.6
B13	0.0000	0.0007	0.0083	-0.0017	13.7759	6.3281	74.7374	80,920.8
B14	0.0000	0.0006	0.0035	-0.0018	110.7876	1.2391	7.3945	854.0
B15	0.0001	0.0007	0.0033	-0.0078	13.8242	-3.0624	43.5118	27,513.8
				After Call Auction Suspension				
A 1	0.0000	0.0008	0.0100	-0.0051	18.1015	4.4240	66.8113	62,263.8
A 2	0.0000	0.0005	0.0052	-0.0017	149.1296	3.2508	31.5223	14,200.8
A 3	-0.0001	0.0005	0.0018	-0.0021	8.6844	-0.2167	1.6656	40.6
A 4	0.0000	0.0013	0.0021	-0.0185	44.1214	-10.6914	136.4282	261,416.2
A 5	0.0000	0.0006	0.0054	-0.0017	18.8038	2.5959	27.3576	10,661.7
A 6	0.0001	0.0010	0.0098	-0.0061	12.3625	2.4213	37.3395	19,434.2
A 7	0.0001	0.0007	0.0081	-0.0014	9.9972	4.1789	42.8090	26,079.6
A 8	0.0000	0.0005	0.0033	-0.0014	82.4192	1.2665	6.3058	633.0
A 9	0.0001	0.0005	0.0045	-0.0010	6.7947	2.7956	22.8939	7,636.6
A10	0.0000	0.0006	0.0048	-0.0019	15.2415	1.5164	15.4323	3,401.1
A11	-0.0001	0.0007	0.0073	-0.0028	11.4112	2.8776	31.3412	13,919.3
A12	0.0000	0.0006	0.0016	-0.0032	18.3023	-0.7738	2.6078	126.1
A13	0.0000	0.0004	0.0015	-0.0013	68.5241	0.1722	0.3716	3.5
A14	0.0000	0.0004	0.0015	-0.0012	360.6461	0.3948	1.6999	48.3
A15	0.0000	0.0004	0.0016	-0.0020	23.6199	-0.2304	3.8433	205.4

The fifteen trading days prior to the suspension of the call auction are superseded with a B (Before) whilst the other trading days are denoted with an A (After). Descriptive statistics for *each* trading day are based on around 340 observations for the call auction period, and 330 observations for the (post-auction suspension period). The Jarque-Bera test for normality, is $\chi^2(2)$ distributed. The critical values are 9.21, 5.99 and 4.61, for the 99%, 95% and 90% confidence levels respectively. The null hypothesis of a normal *distribution is rejected at the 99% level of confidence for all return series, except for A13* where the null hypothesis cannot be rejected.

Table 5.2: Unit Root Tests for Intra-Day Data Sets (One-Minute Frequency)

Day	ADF(1)	95% CV	# Obs.	Day	ADF(1)	95% CV	# Obs.
B 01	-10.250	-2.8703	338	A 01	-13.020	-2.8706	327
B 02	-13.140	-2.8703	337	A 02	-14.050	-2.8706	327
B 03	-9.570	-2.8703	337	A 03	-10.240	-2.8706	327
B 04	-11.150	-2.8703	336	A 04	-23.680	-2.8706	327
B 05	-11.590	-2.8703	338	A 05	-9.620	-2.8705	328
B 06	-10.220	-2.8703	335	A 06	-9.030	-2.8706	327
B 07	-8.300	-2.8703	338	A 07	-11.070	-2.8706	327
B 08	-10.230	-2.8703	336	A 08	-12.140	-2.8706	327
B 09	-13.980	-2.8703	337	A 09	-13.590	-2.8705	328
B 10	-11.850	-2.8703	337	A 10	-9.670	-2.8705	328
B 11	-10.830	-2.8703	336	A 11	-13.750	-2.8706	327
B 12	-10.720	-2.8703	336	A 12	-10.400	-2.8706	327
B 13	-13.700	-2.8703	336	A 13	-10.120	-2.8705	328
B 14	-9.670	-2.8703	335	A 14	-11.050	-2.8705	328
B 15	-8.280	-2.8702	339	A 15	-9.950	-2.8706	327

The table shows Augmented Dickey-Fuller test statistics, on the null hypothesis of a unit root in the intra-day log returns series. A first order Augmented Dickey-Fuller test without a trend was selected. The ADF(1) statistic is the t-ratio of α_1 in the model $\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \beta_1 \Delta X_{t-1} + \varepsilon$. The 95% critical values of the test are shown in MacKinnon (1991). The null hypothesis of a unit root in the data is rejected across all sets. The columns denote the following: Trading Day, ADF Test Statistic, 95% Critical Value, and the Number of Observations used in the test.

5.5.2 Day-of-The-Week Effects in Opening Volatility

This study considers day-of-the-week effects since a look at the opening volatility on Mondays may give valuable insights as to whether NSE volatility is news-related or otherwise. We start by inquiring whether the opening standard deviation of Nifty price level series varies across trading days. The opening standard deviation was computed through the initial 40 observations sampled at one-minute intervals for the particular day. Given that t-tests may cause problems when applied to non-normal distributions such as the ones under review, a non-parametric test is used. This is the Kruskal-Wallis test which is defined by:

$$H = \left[\frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{(TR_i)^2}{n_i} \right] - 3(n+1) \quad \sim \quad \chi^2(k-1) \tag{5.4}$$

where n is the number of observations (in our case 30 trading days), k is the number of groups (in our case Monday - Friday), TR_i is the sum of rankings obtained for each group, and n_i is the number of observations within the particular group.

The standard deviations were ranked, assigning a value of 1 to the lowest standard deviation, and a value of 30 to the highest one. The ranks were then grouped according to the days of the week. For each of the five groups, the sum and the count of ranks was calculated. This yielded an H-statistic of 2.602. Comparing this to the $\chi^2(4)$ critical value (95%) does not allow us to reject the null hypothesis that the opening standard deviations are the same across trading days.

As an alternative methodology, a regression was run over the opening standard deviations of Nifty level series:

$$\sigma_{NFT,OP} = \psi + \beta_1 D_{TU} + \beta_2 D_W + \beta_3 D_{TH} + \beta_4 D_F + \xi \qquad (5.5)$$

where $\sigma_{NFT,OP}$ is the opening standard deviation of the Nifty observations, D_{TU}, D_W, D_{TH}, and D_F are dummy variables for Tuesday, Wednesday, Thursday and Friday, ψ, β_1, β_2, β_3, and β_4 are estimated coefficients, whilst ξ is an error term.[32]

When considering that this regression was estimated using only 30 observations and that it includes four dummy variables, one cannot expect highly significant results. The results reported in Table 5.3 Panel A show that all dummy variables are negative, indicating that the opening volatility is somewhat higher on Mondays, but the coefficients are not significant at the 95% confidence level.

A second regression was run, this time using the Nifty (levels) percentage squared returns, which were sampled at one-minute intervals. The opening returns were calculated using the initial forty Nifty price observations for the particular day. The estimated regression was:

$$R^2_{NFT,OP} = \pi + \beta_1 D_{TU} + \beta_2 D_W + \beta_3 D_{TH} + \beta_4 D_F + \xi \qquad (5.6)$$

[32] This model is a variation of the one estimated by French (1980), who analysed stock returns (rather than standard deviations).

where $R^2_{NFT,OP}$ denotes the opening squared (percentage) one-minute returns of the Nifty observations; D_{TU}, D_W, D_{TH}, and D_F are dummy variables for Tuesday, Wednesday, Thursday and Friday respectively; π, β_1, β_2, β_3, and β_4 are estimated coefficients, whilst ξ is an error term.

Table 5.3: Regressions of Day-of-The-Week Effects of Opening Volatility

Panel A: (Opening Standard Deviations Sampled at Daily Frequency)

ψ	D_{TU}	D_W	D_{TH}	D_F
5.44940 *** (5.01)	-2.54181 * (1.78)	-1.03257 (0.72)	-2.55010 * (1.73)	-1.89576 (1.23)
Number of Observations: 30		R^2: 0.1543		R-bar-squared: 0.0190

Panel B: (Opening Returns Sampled at One-Minute Frequency)

π	D_{TU}	D_W	D_{TH}	D_F
0.0000044 *** (4.70)	-0.0000032 *** (2.64)	-0.0000022 * (1.84)	-0.0000032 *** (2.58)	-0.0000031 ** (2.34)
Number of Observations: 1170		R^2: 0.0079		R-bar-squared: 0.0045

Panel A shows the results for the regression where the dependent variable was the Standard Deviation of the first 40 observations of the Nifty Index. Panel B shows the results for the regression where the dependent variable consisted of the initial 39 Nifty (levels) squared % returns sampled at one-minute intervals, across 30 trading days.

The first column shows the intercept, whilst columns 2-5 show the dummy variables for Tuesday, Wednesday, Thursday and Friday. The coefficients are shown on top, with t-ratios in brackets underneath. Significance at the 99%, 95% and 90% levels is denoted by ***, ** and * respectively.

The results are shown in Table 5.3 Panel B. Again the dummy variables are all negative indicating that opening squared returns (and therefore volatility) are higher on Mondays. The dummy variables are all significant at the 95% - 99% level of confidence except for the D_W which is significant at the 90% level of confidence.[33]

Overall the latter results confirm that the opening volatility tends to be higher on Mondays, albeit not clearly significant through the cross-section of tests.[34]

[33] This indicates that the Wednesday (opening) volatility is the second highest during the weekdays, after the Monday (opening) volatility. This result may be related to the NSE settlement system during the particular period, whereby most of the trades occurring during the week were settled on Tuesdays. Following the arguments of Bildik (2001), buyers have an incentive to trade on Wednesdays given that they would not be required to settle their trades prior to six days.

[34] The evidence shown in Table 5.3 somewhat contradicts the observations of Choudhry (2000) who did not find significant evidence of higher Monday volatility on the Indian market. These different results may be reconciled when considering that the latter study featured a different index and it did not specifically look at the *opening* volatility. A further possible explanation for the conflicting results is that Choudhry's study used a data set ranging from 1990-1995, whereas this study used 1999 data. As outlined by Fox *et. al.* (1999), India's capital markets have undergone substantial change during the 1990's, including more rigorous reporting requirements for companies. Higher reporting standards may induce higher volatility on Mondays as outlined by Foster and Viswanathan (1990).

Following French's (1980) assertion that Monday opening returns tend to be predominantly negative since firms delay the release of unfavourable information till after the closing of the exchange on Friday, a further regression was estimated. The dependent variable consisted of the Nifty (levels) percentage initial returns (sampled at one minute intervals) as a function of dummy variables for Tuesday – Friday. If the information accumulated on Monday mornings tends to be unfavourable, we should note that Monday initial returns are lower than those of the rest of the days. The results shown in Table 5.4 indicate that Monday returns do not tend to be predominantly negative, since the intercept is positive and none of the dummy variables denoting the rest of the trading days are significant.

Table 5.4: Regressions of Day-of-The-Week Effects of Opening Returns Sampled at One-Minute Intervals

π	D_{TU}	D_W	D_{TH}	D_F
0.000074 (0.74)	-0.000012 (0.09)	-0.000126 (0.96)	0.000007 (0.06)	-0.000030 (0.21)
Number of Observations: 1170		R^2: 0.0014		R-bar-squared: -0.0021

The dependent variable consisted of the initial 39 Nifty (levels) percentage returns sampled at one-minute intervals, across 30 trading days. The first column shows the intercept, whilst columns 2-5 show the Dummy variables for Tuesday, Wednesday, Thursday and Friday. The coefficients are shown on top, with t-ratios in brackets underneath. None of the coefficients are significant. Results show that Monday opening returns are not significantly different from the opening returns of the rest of the week.

Considering the possibility that Monday opening returns are not predominantly negative due to noise induced by high-frequency sampling, the cumulative opening return for the index (during the first 40 minutes) was estimated for each trading day in the sample. An average return for day of the week was then worked out, as shown in Table 5.5. The table confirms that Monday opening returns do not tend to be "more negative" than the opening returns for the other days of the week.

The tests undertaken so far indicate that the opening volatility on Monday tends to be somewhat higher than that of the rest of the days, although the difference is not clearly significant. In addition, Monday opening returns are not predominantly negative.

In view of the findings of Madureira and Leal (2001), that a Monday effect may be present in index data, but not in individual stock prices, additional tests were carried out on individual stock data. The aim is to establish whether the higher Monday volatility is confirmed when analysing individual stocks. A sample of nineteen out of fifty stocks included in the NSE Nifty Index was selected. The latter stocks were selected in a way to capture a variety of industries, but otherwise the sample selection process was random. The sample period for individual stock data ranged from the 1st January 1999 to 31st December 2003 – a total of 1257 observations. Volatility was assessed in terms of the Scaled Intra-Day Price Difference, which was defined as follows:

$$D_{i,t} = (P_{high\ i,t} - P_{low\ i,t}) \ / \ P_{open\ i,t} \qquad (5.7)$$

where $P_{high\ i,t}$, $P_{low\ i,t}$ and $P_{open\ i,t}$ are the highest, lowest and opening prices for stock i on day t respectively. Therefore this test considers the volatility throughout the *whole* trading day, rather than the *opening* volatility.

Table 5.5: Average Opening Returns for Different Days of the Week

Day of the Week	No. of Trading Days Sampled	Average Opening Return
Monday	5 days	0.16%
Tuesday	7 days	0.25%
Wednesday	7 days	-0.22%
Thursday	6 days	0.58%
Friday	5 days	0.12%

The opening return for a particular trading day was defined as the Nifty Index % return for the first 40 minutes of the day. The average for the particular opening return for each day of the week was then estimated. Monday returns do not tend to be predominantly negative as compared to other trading days.

The following regression was estimated:

$$D_i = \pi_i + \beta_i D_{MON,i} + \xi_i \qquad (5.8)$$

where D_i, is the Scaled Intra-Day Price Difference for stock i, π and β are estimated coefficients, $D_{MON,i}$ is a dummy variable which takes the value of 1 on a Monday and zero otherwise, whilst ξ_i is an error term. Higher Monday volatility should result in a significantly positive coefficient for the dummy variable. The results reported in Table 5.6 show that volatility for the sampled stocks is not significantly higher on Mondays; indeed $D_{MON,i}$ is negative in case of eight stocks.

Thus, Monday volatility seems somewhat higher as compared to other weekdays when considering Nifty Index data, whilst it is not significantly higher when measured in relation to individual stocks. Whilst this "inconsistency" might be partly due to the fact that the tests on the Nifty Index data considered the opening Monday volatility, whilst the tests on the individual stocks considered the volatility throughout the whole day, the results still allow us to conclude that the Monday effect in the index data is not related to information. If the Monday effect was indeed related to information, it should still have shown up in the individual stock data, given that one may expect information-related fluctuations to be of a longer term nature and thus showing up when considering volatility estimates in respect of the whole trading day.

Table 5.6: Individual Stock Volatility Regressions on a Monday Dummy Variable (estimated through daily-frequency data)

Sampled Stock	Intercept	Monday Dummy Variable		R-Squared
		Coefficient	*t-Ratio*	
Bajajauto	0.03746	0.0014	(0.82)	0.00054
Bhel	0.04702	-0.0026	(1.42)	0.00160
Bpcl	0.04921	-0.0017	(0.82)	0.00054
Bses	0.04120	0.0007	(0.36)	0.00010
Colgate	0.03074	0.0021	(1.49)	0.00176
Digitaleqp	0.06041	-0.0014	(0.55)	0.00024
Gujambcem	0.04236	-0.0018	(1.03)	0.00084
Herohonda	0.04371	-0.0001	(0.08)	0.00001
Hindlever	0.03262	0.0003	(0.24)	0.00005
Icicibank	0.04957	-0.0004	(0.19)	0.00003
Ipcl	0.04679	0.0003	(0.16)	0.00002
L&T	0.04136	0.0003	(0.16)	0.00002
M&M	0.04734	-0.0001	(0.05)	0.00000
Niit	0.06052	0.0003	(0.12)	0.00001
Orientbank	0.04275	0.0021	(1.11)	0.00098
Reliance	0.03552	0.0012	(0.73)	0.00042
Sbin	0.03694	0.0006	(0.42)	0.00014
Sunpharma	0.04643	-0.0025	(1.15)	0.00106
Tatatea	0.04148	0.0013	(0.70)	0.00039

The table shows results for volatility regressions for a sample of 19 stocks. Volatility measured as the Scaled Intra-Day Price Difference, was regressed on an intercept, a dummy variable taking the value of 1 on a Monday, and a value of zero otherwise, as well as an error term. Each regression for the individual stocks was estimated using a sample of 1257 observations. The table reports the Intercept Value, and the Coefficient and t-ratio for the Dummy Variable. R-squared statistics are shown in the last column. The dummy variable does not indicate that volatility is significantly higher on Mondays.

Thus overall the explanation proposed by Madureira and Leal (2001), seems applicable in the context of the Nifty Index. The Monday effect transpires in the index data but disappears when considering individual stocks. This is probably due to index construction features and market factors such as non-synchronous trading. Overall, it is unlikely that the higher index volatility on Mondays is related to information flows.

5.6 Monthly Volatility

The study now turns to the analysis of monthly volatility through daily log returns. Higher volatility during the month of March and in the subsequent period might be justified on the grounds that the financial year for a large number of Indian companies terminates in March.

5.6.1 Analysing the Data Set

The plots of the daily Nifty (levels) series and log returns for the period 1st January 1999-31st December 2003 are shown in Figure 5.2. The latter plot visually confirms that high volatility seems to cluster around specific periods. Nifty Log Returns feature an excess kurtosis of 2.6138 and a negative skewness of -0.17354. A Jarque-Bera Test Statistic of 363.84 permits the rejection of the null hypothesis of normality at the 99% level of confidence when compared to the respective Chi-Squared critical value.

The first order autocorrelation coefficient of the log returns is highly significant, whilst the majority of the subsequent lags are insignificant. The autocorrelation function is shown in Figure 5.3. The Augmented Dickey-Fuller test-statistics yielded similar statistics when specifying tests with and without a trend. ADF tests yielded statistics of -25.05 (Order 1), -14.4 (Order 5), and -10.1 (Order 10). Order 5 and order 10 tests were specified due to possible weekly or fortnightly effects in the data. Comparing the former statistics to the 95% critical value of -2.86 allows us to reject the Null Hypothesis of a Unit Root in log returns.

The time series spans around 5 years and should enhance the robustness of the fitted regressions; yet as outlined in Chapter 2 there are limitations inherent in working with such a long time period. In particular the data set includes changes in market microstructure, which are not accounted for. Some of these microstructure changes (for instance changes in price limits) may well affect the underlying volatility process.

Figure 5.2: Time Series Plots for (a) Nifty Index and (b) Nifty Log Returns

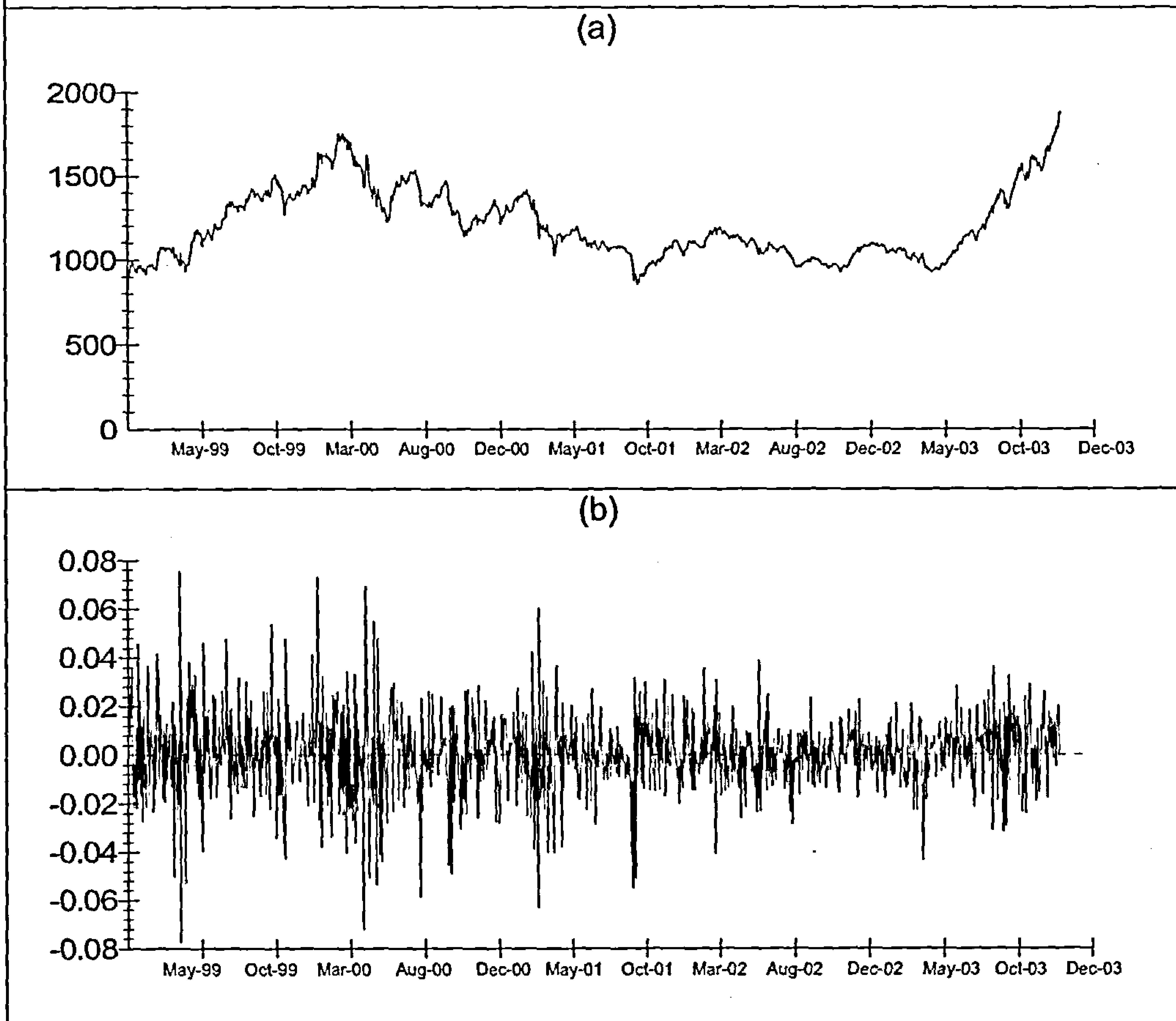
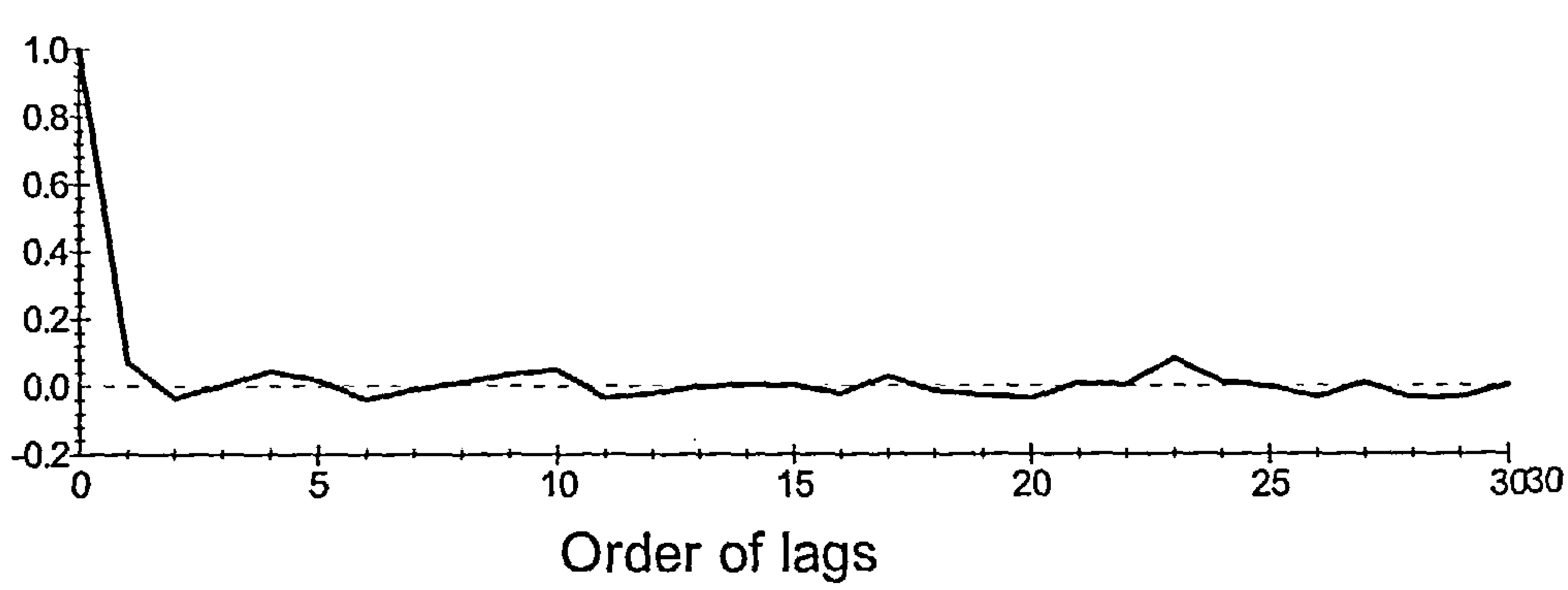


Figure 5.3: Autocorrelation Function for Nifty Log Returns



5.6.2 Monthly Seasonality on NSE

The test on monthly seasonality is related to the previous one on day-of-the-week effects, in that the main scope is not the simple detection of seasonality, but rather to serve as an indication of whether volatility is related to news (and therefore is partly justified) or whether it constitutes excessive market movements. This follows the notion that the Indian fiscal year and the accounting year for a large number of NSE-quoted companies end in March, and annual reports are released between March and June. In this way, higher volatility during these months indicates that market movements may constitute a response to new information. If no significant differences in volatility or returns are found around these months, it would imply that the market tends to be excessively volatile for most of the year (since the volatility of the "no news months" is equal to the volatility of the "news months").

The test consists of two simple OLS regressions, where two different proxies for volatility were specified as dependent variables, whilst the explanatory variables in each regression were eleven dummy variables for the months of February, March.... December. The dependent variable in the first regression was the Modulus of the Daily Log Returns as a volatility proxy, whilst the dependent variable in the second regression was the Intra-Day Scaled Difference (Equation 5.7).

Regression results are shown in Table 5.7. The R^2 statistics indicate that the models have low explanatory power, but this may be expected when explaining volatility in terms of an intercept and a rudimentary pattern of information flow – one should really account for a more detailed pattern of information to obtain comprehensive explanatory power.

Prior to discussing the volatility around the month of March, we note that the dummy variable denoting the month of August shows a reduction in volatility during this period, and this is significant at the 95% level of confidence. We may attribute this to a holiday effect; for instance Janssen (2004) who analysed news release patterns for US economic indicators found a tendency for less news releases during August. Bouman and Jacobsen (2002) presented similar evidence of lower holiday-period volatility in respect of a number of emerging and developed markets. The authors stated that differences across the holiday months of May to October do not emanate from differences in trading volume, but possibly from changes in trading behaviour such as the degree of risk aversion or increased liquidity requirements.

Table 5.7: Monthly Seasonality of Volatility Regressions (estimated through daily data)

Volatility Proxy	**Regression 1** *Modulus of Log Returns*		**Regression 2** *Intra-Day Scaled Difference*	
	Coefficient	*T-ratio*	*Coefficient*	*T-ratio*
Intercept	0.0116 ***	(11.25)	0.0207 ***	(17.52)
Dummy Variables:				
February	0.0001	(0.09)	0.0007	(0.43)
March	0.0027 *	(1.85)	0.0076 ***	(4.50)
April	0.0052 ***	(3.49)	0.0086 ***	(5.02)
May	0.0013	(0.91)	0.0026	(1.53)
June	-0.0013	(0.91)	-0.0016	(0.94)
July	-0.0017	(1.18)	-0.0016	(0.99)
August	-0.0029 **	(1.99)	-0.0039 **	(2.31)
September	0.0018	(1.22)	0.0023	(1.36)
October	0.0002	(0.11)	0.0014	(0.83)
November	-0.0014	(0.95)	-0.0020	(1.16)
December	-0.0020	(1.35)	-0.0015	(0.88)
Regression Statistics	R^2	0.0405	R^2	0.0802
	R-bar ^{2}	0.0320	R-bar ^{2}	0.0720
	F-statistic	4.7728	F-statistic	9.8644
	#. Observations	1256	#. Observations	1257

In the above models, volatility is measured in terms of the Modulus of Log Returns in the first regression, whilst it is measured in terms of the Intra-Day Scaled Difference in the second regression. The explanatory variables are dummies for the months of February to December. Statistical significance is denoted by ***, **, and * for the 99%, 95% and 90% levels of confidence respectively.

As expected, significant increases in volatility are evident during the months of March and April, and we may attribute these to an end-of-accounting-year effect and an end-of-fiscal year effect. The increased volatility during April is significant at the 99% level of confidence in both models. Yet, the increased volatility for the month of March is significant at the 99% level when modelled in terms of the Intra-Day Scaled Difference, but it is only significant at the 90% level when modelled in terms of the modulus of log returns.

This might be disclosing an interesting feature, in that the increased volatility during the month of March might include a comprehensive amount of unjustified movements. Whilst March volatility increases sharply in terms of the intra-day scaled difference (which may be interpreted as movements around the fundamental value of the stock price), the increase is not as sharp in terms of daily returns. This implies that the increased price movements during the day might not have sufficient economic justification; these fluctuations are short-lived and do not materialise in a similar jump in returns of the same statistical significance. Thus, the increased volatility during this month may be interpreted as the response to conjectures of traders about the performance of companies at year-end, when preliminary results and audited accounts have not yet been published. Part of these responses are "unfounded guesses" and therefore they do not necessarily result in a long-lived change in the magnitude of returns.

Volatility increases during the month of April at the 99% level of confidence both when modelled in terms of log return modulus, and when modelled in terms of the Intra-Day Scaled Difference. This may imply that the market movements during this month are long-lived since they materialise in longer-term returns of comparable statistical significance and therefore have a higher degree of economic justification. Thus, we may interpret the April volatility as responses to "real news" following clustering of earnings reports.

In summary, NSE witnesses increased volatility during the months of March and April, which coincides with the end of the accounting year for a large number of quoted companies. The increased volatility during March may be the response to "guesses" about company performance, since the increased price dispersion does not materialise in a change in returns of similar statistical significance. The increased volatility during April is more likely to consist of responses to real news about company performance, since the increased price dispersion results in a change of similar significance in returns. Volatility abates during the month of August (in line with other markets) when traders are likely to be on holiday.

In order to present the above notions through more parsimonious models, two further regressions were estimated as follows:

$$Y = \pi + \beta_1 D_{MAR,APR} + \beta_2 D_{AUG} + \xi \qquad (5.9)$$

where $D_{MAR,APR}$ is a dummy variable which takes the value of 1 during March and April and zero otherwise, D_{AUG} is a dummy variable which takes the value of 1 during August and zero otherwise, π, β_1 and β_2 are estimated coefficients, whilst ξ is an error term. In the first regression, the dependent variable was the modulus of the daily log returns, whilst in the second regression the dependent variable was the Scaled Intra-Day Price Difference. Results shown in Table 5.8 confirm the above intuitions that volatility is significantly higher during March and April, whilst it is significantly lower during August.

Given the limitations of the dummy variable methodology when assessing monthly seasonality as described in Section 5.3.1, the Kruskal-Wallis test was used as a non-parametric alternative. This is defined by Equation 5.4 reproduced hereunder:

$$H = \left[\frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{(TR_i)^2}{n_i} \right] - 3(n+1) \quad \sim \quad \chi^2(k-1) \qquad (5.4)$$

where n is the number of observations (in our case 1257 for the Scaled Intra-Day Price Difference and 1256 for the Modulus of Daily Log Returns), k refers to the three different groups (i.e. the March-April period, August, and Rest of The Year), TR_i is the sum of rankings obtained for each group, and n_i is the number of observations within the particular group.

Table 5.8: Monthly Seasonality of Volatility Regressions (Parsimonious Models estimated through daily data)

Volatility Proxy	Regression 1 *Modulus of Log Returns*		Regression 2 *Intra-Day Scaled Difference*	
	Coefficient	*T-ratio*	*Coefficient*	*T-ratio*
Intercept	0.0113 ***	(32.58)	0.0207 ***	(52.05)
Dummy Variables:				
March-April	0.0043 ***	(5.16)	0.0080 ***	(8.45)
August	-0.0026 ***	(2.35)	-0.0039 ***	(3.10)
Explanatory Statistics	R^2	0.0279	R^2	0.0667
	R-bar ^{2}	0.0264	R-bar ^{2}	0.0652
	F-Statistic	18.011	F-Statistic	44.800
	#. Observations	1256	#. Observations	1257

In the above models, volatility is measured in terms of the Modulus of Log Returns in the first regression, whilst it is measured in terms of the Intra-Day Scaled Difference in the second regression. The first explanatory variable is a dummy taking a value of 1 during March & April and zero otherwise, and the second explanatory variable is a dummy taking a value of 1 during August and zero otherwise. Statistical significance is denoted by *** for the 99% level of confidence.

The modulus of log returns and intra-day scaled differences were respectively ranked, assigning a value of 1 to the lowest value. The ranks were then grouped into three, and the sum and the count of ranks was calculated for each group. This yielded an H-statistic of 20.00 for the Modulus of Log Returns, and an H-statistic 55.39 for the Scaled Intra-Day Price Difference. When comparing the H-statistics to the $\chi^2(2)$ critical value, we may reject the null hypothesis that the volatility is the same across the three periods at the 99% level of confidence.

Overall, the above tests indicate that volatility is significantly higher during the months of March and April, and significantly lower during August. These findings are of noteworthy importance, since they hint that the infamous January effect – absent in the Indian context but present in most other markets – may in fact be related to the end-of-financial-year of quoted companies and possibly the end of fiscal year, since a similar "January" effect is witnessed during the months of March and April on the Indian markets.[35]

5.7 The Connection Between NSE Volatility and Returns

The third empirical investigation concerns the relationship between volatility risk and return, as inferred through EGARCH-in Mean (EGARCH-M) models. Section 5.7.1 considers the basic features of the data, consisting of Nifty daily log returns for the period 1st January 1999 to 31st December 2003. A preliminary EGARCH model is fitted in the subsequent section, whilst Section 5.7.3 investigates the relationship between volatility and returns through EGARCH-M models.

5.7.1 Preliminaries for Specifying the GARCH Model

Two important elements in estimating GARCH models relate to the definition of the return-generation process (say, an AR model), and whether the conditional variance equation should account for any asymmetric effects in the data.

In selecting the return-generation process, six AR(ρ) models were estimated with ρ ranging from 0 to 5 in order to infer the model which best captures the return generating process. The Schwarz Bayesian Criterion selected the AR(1) process as the best model, whilst the Akaike Information Criterion selected the AR(2) process. Yet according to the latter criterion, the

[35] One side-issue relating to these changes in volatility is whether a January effect might show up, after omitting the data of the months showing significant volatility changes (i.e. March, April and August). Eliminating these months from the data set, the January effect still does not transpire in terms of significant dummy variables when volatility is modelled in terms of the Modulus of Log Returns and the Intra-Day Scaled Difference. This indicates that the main cause of the January effect observed on other markets is likely to be the end-of-financial-year of listed companies and end of fiscal years. This evidence potentially contrasts with the results of Clare, Psaradakis and Thomas (1995) who noted both a January effect and seasonality around fiscal year end in April, in the context of the UK equity markets.

difference between the statistic for the AR(1) and AR(2) process was minimal and therefore the log return series was modelled as an AR(1) process for the sake of parsimony.

The presence of ARCH effects in the residuals of the AR(1) process was tested for through LM heteroskedasticity tests as proposed by Engle (1982).[36] Order 1 and order 5 tests yielded LM statistics of 89.7 and 108.6 respectively. The tests permit the rejection of the Null Hypothesis of no ARCH effects at the 95% level of confidence, when comparing the LM statistics to the Chi-Squared statistics at the respective degrees of freedom.

In order to infer the level of asymmetry in the conditional volatility, the methodology proposed by Engle and Ng (1993) was used. The squared error term of the AR(1) process is regressed over a constant, a dummy variable of the lagged sign and an error term:

$$\varepsilon_t^2 = \phi_0 + \phi_1 D_{t-1}^- + \xi_t \tag{5.10}$$

When ε_{t-1} is negative D^-_{t-1} takes a value of 1, whilst it takes a value of zero otherwise. Significance of D^-_{t-1} is an indication of asymmetric volatility. The coefficient of D^-_{t-1} was 0.000073 with a t-ratio of 2.36 and this is significant at the 95% level of confidence. This means that negative returns tend to be followed by higher volatility, and therefore it is desirable to use models which account for this feature. This is in line with the result discussed in Chapter 3 that high volatility tends to follow negative returns.

The selected asymmetric volatility model was Exponential GARCH (EGARCH) as proposed by Nelson (1991). EGARCH processes model the log of conditional variance as follows:

$$\ln(h_t) = \omega + \alpha_1 z_{t-1} + \gamma_1 \left(|z_{t-1}| - E(|z_{t-1}|)\right) + \beta_1 \ln(h_{t-1}) \tag{5.11}$$

where h_t is the conditional variance, and z_{t-1} is the lagged error term. Given that Equation (5.11) is modelling the logarithm of the conditional variance, and that the inverse log function (the exponential) of any number is always positive, no restrictions need to be imposed on the estimated coefficients to ensure a positive conditional variance. However, $|\beta_1|$ has to be less than one in order to ensure process stability.

[36] This test was described in Section 3.4.3.

Positive errors have an impact of $\alpha_1+\gamma_1$ on $\ln(h_t)$, whilst negative errors have an impact of $\alpha_1-\gamma_1$. A further asymmetric effect of positive and negative errors on volatility also results from the asymmetric shape of the exponential curve.

5.7.2 Estimating an EGARCH Process

A preliminary EGARCH model was fitted to the daily data, assuming that the conditional distribution of the errors was normal. The results are shown in Table 5.9 Panel A. The AR(1) coefficient of the Log Return Equation is highly significant – this indicates that past returns may be used to (partly) predict current returns and therefore following Fama (1970), we may argue that the market is not even weak-form efficient.[37] All the coefficients of the heteroskedasticity equation are highly significant. The latter coefficients imply that a positive shock (say +1) in period $t-1$ has an impact of around 0.17 on the log of the conditional variance in period t. A negative shock (say -1) in period $t-1$ has an impact of around 0.38 in period t. These shocks then drag on to period $t+1$ through the β coefficient. The β coefficient is highly significant and shows that around 93% of current period conditional volatility is transmitted to the next period. This implies that the change in conditional variance prevailing in period t due to the shock z_{t-1}, has a significant impact on the conditional variance of period $t+1$, and thus we may state that there is a substantial degree of persistence. This AR process in the conditional variance then continues in the subsequent periods. Authors such as Janssen (2004) interpreted significant β coefficients as the markets' response to news, given that some types of news follow an autoregressive pattern. The combined effects of shocks and persistence on the conditional variance are summarised in Table 5.9 Panel B.

Despite the significance of the coefficients, one should note that the explanatory power of the regression in terms of the R^2 statistics is low. In addition, the low F-statistic for the log return equation does not permit the rejection of the null hypothesis that the estimated coefficients are equal to zero. Yet this may be expected when specifying a regression which explains returns through an AR process. Returns are likely to depend mainly on the underlying news – which are not accounted for in this setup. Despite this, the overall model captures (at least part of)

[37] Fama (1970) described three forms of market-efficiency. A market is "weak-form" efficient if past information is not relevant in predicting returns, it is "semi-strong form" efficient if public information is not relevant in predicting returns, and it is "strong-form" efficient if neither public nor private information are relevant in predicting returns.

the heteroskedasticity of returns, in view of the significance of the coefficients of the conditional variance equation as well as the Wald-Statistic (Table 5.9 Panel A).

Table 5.9: EGARCH Model fitted to Nifty Daily Log Return Data

Panel A: Regression Results

Log Return AR(1) Process:

Intercept	Lag	R {bar} ^{2}	F-Statistic: F (4,1250)
0.00056	0.12372 ***	0.0023	0.71927
(1.45)	(4.13)	{-0.0009}	

Conditional Variance Equation:

Intercept: ω	Coeff: α_1	Coeff: γ_1	Coeff: β_1
-0.5683 ***	-0.1054 ***	0.2753 ***	0.9321 ***
(3.94)	(4.73)	(7.26)	(54.83)

Wald Test Statistic for the Null Hypothesis that $\alpha_1 + \gamma_1 + \beta_1 = 0$:
697.4 as compared to a Chi Squared (1) Critical Value of 6.635 at the 99% level of confidence.

Model estimation based on 1255 observations.

Panel B: Impacts of Shocks and Persistence on Conditional Variance

Direct Impact of a ±1 unit shock in z_{t-1} on log h_t *assuming that* $E(z_{t-1})=0$		**Indirect Impact of change in log h_t (due to ±1 unit shock in z_{t-1}) on log h_{t+1}**	
Positive Shocks	**Negative Shocks**	**Positive Shocks**	**Negative Shocks**
$z_{t-1}(\alpha_1 + \gamma_1)$	$z_{t-1}(\alpha_1 - \gamma_1)$	$\beta_1(\Delta \log h_t)$	$\beta_1(\Delta \log h_t)$
0.1699	0.3807	0.1584	0.3549

Panel A shows the results for the estimated EGARCH process. The t-ratios are shown in brackets underneath the respective coefficients. Significance at the 99% level of confidence is denoted by ***. The Adjusted R^2 is shown in braces underneath the R^2 statistic. Panel B shows comparative statistics by tracing the effects of a shock in z_{t-1} on subsequent conditional volatility.

Finally, the "goodness of fit" of the estimated model may also be judged visually, as shown in Figures 5.4 to 5.6. The plot of the actual versus fitted values (Figure 5.4) confirms that the fitted model only explains a minor portion of the variation in Nifty Log Returns. Figure 5.5 shows that only a few of the residuals are statistically significant, yet it discloses potential serial correlation in the error terms. The presence of residual serial correlation was confirmed by statistically significant autocorrelation coefficients. When considering the residual series, the correlation coefficient was statistically significant at the first lag (90% confidence level), the tenth lag (90% confidence level) and lag 23 (99% confidence level).[38] This suggests that the EGARCH model does not capture all the dependencies in the mean and variance of the Nifty Index. The histogram of the scaled residuals (Figure 5.6) indicates that the error terms approximate a normal distribution (unlike the leptokurtic distribution of the underlying data set).

Figure 5.4: Plot of Actual and Fitted Values

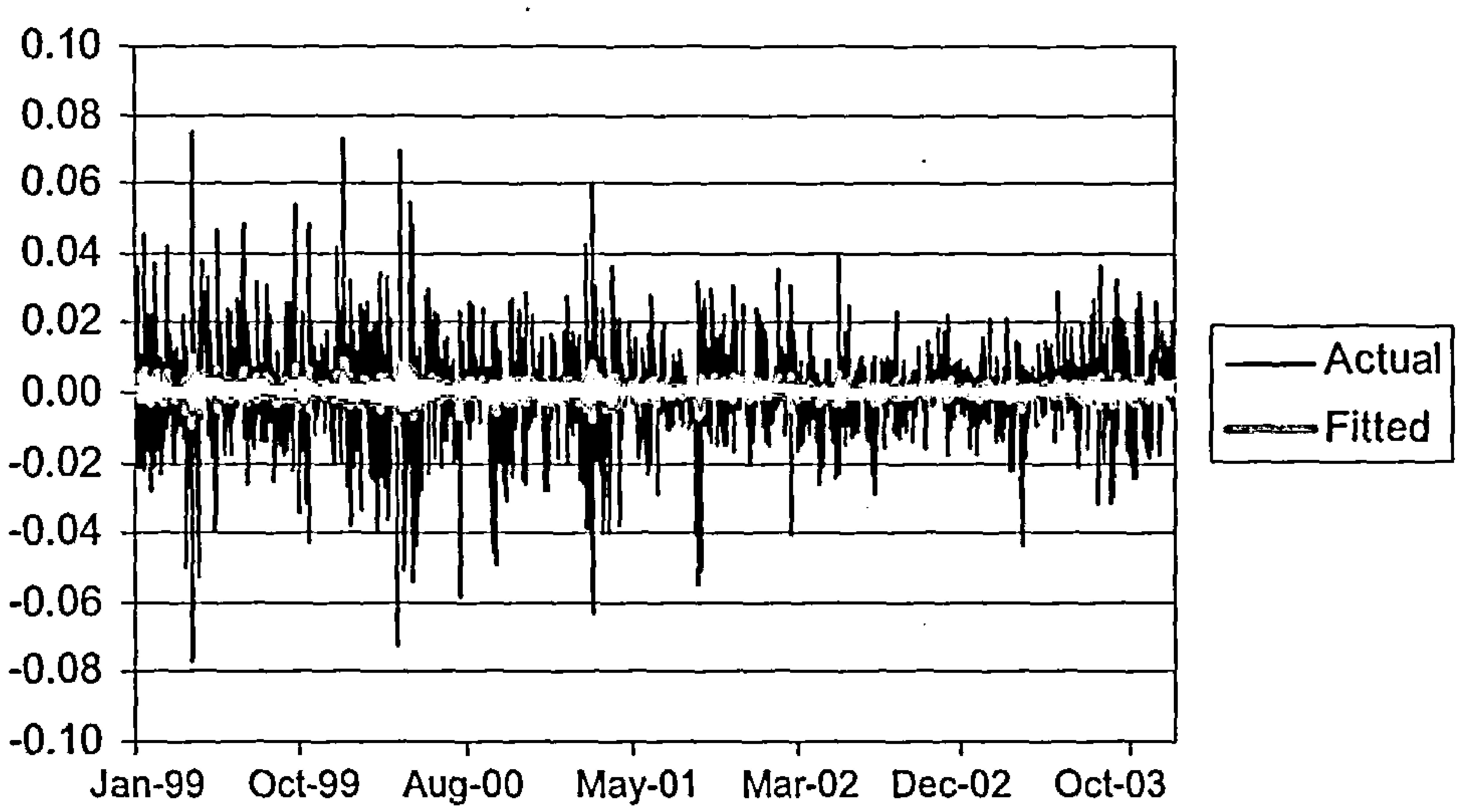
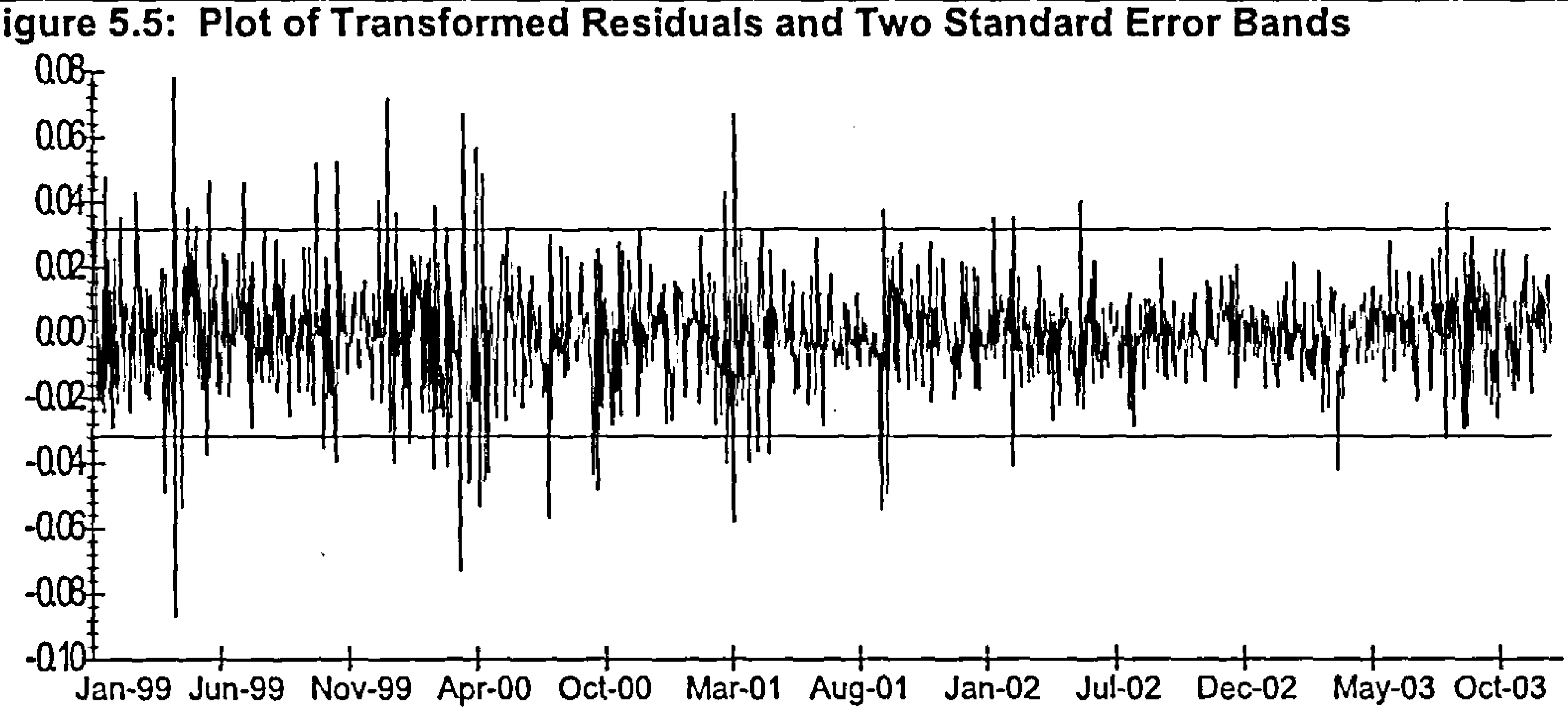
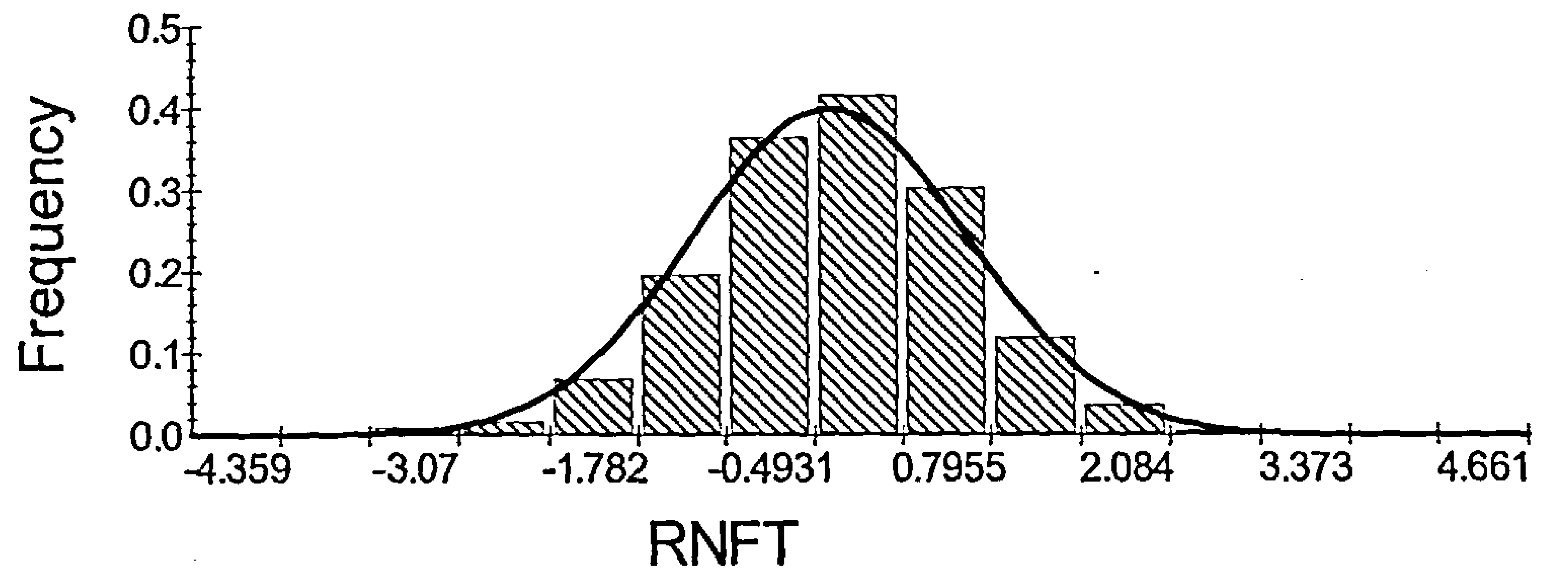


Figure 5.5: Plot of Transformed Residuals and Two Standard Error Bands



[38] The significant serial correlation of the tenth lag is in line with the finding of Bhattacharya, Sarkar and Mukhopadhyay (2003) of fortnightly seasonality in the Indian stock markets, as outlined in Section 5.2.2. The significance of the 23rd lag may denote monthly seasonality, such as a turn-of-the-month effect.

Figure 5.6: Histogram of Scaled Residuals and the Normal Density



5.7.3 Estimating EGARCH-M Processes

EGARCH-M processes model asymmetric volatility as per the EGARCH model, but also seek to explain the return generating process of the mean equation through the conditional variance of returns, postulating a risk-return relationship. The conditional variance equation is the same as shown in Equation (5.11).

Two EGARCH-M models were fitted to the data set, assuming in both cases that the conditional distribution of the errors was normal. The first model specified the mean equation of log returns as an AR(1) process plus an additional variable accounting for the conditional variance as follows:

$$r_t = \varphi + \rho r_{t-1} + \delta h_t + \varepsilon_t \qquad (5.12)$$

The mean equation of the second model simply specified the log returns as a function of an intercept, the conditional variance and an error term as shown in Equation (5.13):

$$r_t = \varphi + \delta h_t + \varepsilon_t \qquad (5.13)$$

The results are summarised in Table 5.10, Panels A and B. The mean equation regressions have low explanatory power as shown by the R^2 and the F-statistics; although the first regression has better explanatory power than the second one. The coefficients for the conditional variance equation are all highly significant and the Wald tests reject the null hypothesis that these coefficients are equal to zero at the 99% confidence level.

Table 5.10: EGARCH-M Models fitted to Nifty Daily Log Return Data

PANEL A (Regression 1):

Log Return Process:

Intercept: φ	Coeff: ρ	Coeff: h_t	R {bar} ^{2}	F-Statistic: F (5,1249)
0.00003	0.1253 ***	2.7764	0.0038	0.9418
(0.04)	(4.15)	(0.74)	{-0.0002}	

Conditional Variance Equation:

Intercept: ω	Coeff: α_1	Coeff: γ_1	Coeff: β_1
-0.6045 ***	-0.1054 ***	0.2762 ***	0.9279 ***
(3.82)	(4.66)	(7.25)	(49.62)

Wald Test Statistic for the Null Hypothesis that $\alpha_1 + \gamma_1 + \beta_1 = 0$:
653.6 as compared to a Chi Squared (1) Critical Value of 6.635 at the 99% level of confidence.

PANEL B (Regression 2):

Log Return Process:

Intercept: φ	Coeff: h_t	R {bar} ^{2}	F-Statistic: F (4,1250)
0.00056	0.2594	0.00007	0.0234
(0.84)	(0.08)	{-0.0031}	

Conditional Variance Equation:

Intercept: ω	Coeff: α_1	Coeff: γ_1	Coeff: β_1
-0.5504 ***	-0.0960 ***	0.2726 ***	0.9341 ***
(3.81)	(4.59)	(7.23)	(54.63)

Wald Test Statistic for the Null Hypothesis that $\alpha_1 + \gamma_1 + \beta_1 = 0$:
766.6 as compared to a Chi Squared (1) Critical Value of 6.635 at the 99% level of confidence.

Panel C: Impacts of Shocks and Persistence on Conditional Variance

Direct Impact of a ±1 unit shock in z_{t-1} on log h_t assuming that $E(z_{t-1})=0$		Indirect Impact of change in log h_t (due to ±1 unit shock in z_{t-1}) on log h_{t+1}	
Positive Shocks	**Negative Shocks**	**Positive Shocks**	**Negative Shocks**
$z_{t-1}(\alpha_1 + \gamma_1)$	$z_{t-1}(\alpha_1 - \gamma_1)$	$\beta_1(\Delta \log h_t)$	$\beta_1(\Delta \log h_t)$
Regression 1			
0.1708	0.3816	0.1585	0.3541
Regression 2			
0.1766	0.3686	0.1650	0.3443

Panels A and B show the results for two alternative EGARCH-M specifications. Both estimations were based on 1255 observations. T-ratios are shown in brackets underneath the respective coefficients. Significance at the 99% level of confidence is denoted by ***. The Adjusted R^2 is shown in braces underneath the R^2 statistic. Panel C shows comparative statistics by tracing the effects of a shock in z_{t-1} on subsequent conditional volatility.

The regressions yield the same qualitative results as regards the relationship between volatility and returns. The AR(1) lag in the first regression is highly significant and again this indicates that the market is not weak-form efficient. The other coefficients of the mean equation are insignificant, and this implies that volatility is not a significant factor in explaining Nifty returns – although the coefficient of h_t in the mean equation is positive (and therefore in the expected direction). This may suggest that the returns on underlying securities do not directly compensate for risk as measured by conditional volatility. In this way, risk-averse investors are better off holding stocks of lower volatility and this also suggests that at least a portion of the underlying stocks may be excessively volatile. Despite this, the fact that the coefficient of h_t is not significant does not imply that the volatility risk of holding the market portfolio is being unrewarded, given the presence of other variables in the mean equation (which generate additional returns).

The combined effects of shocks and persistence on the conditional variance are summarised in Table 5.10 Panel C. Results are similar to those of the EGARCH model estimated in the previous section. The coefficient of β_1 in both equations, as well as the comparative statistics shown in Table 5.10 Panel C point at a relatively high persistence of volatility – again hinting that volatility might be excessive.

The plots of the error terms were qualitatively the same for both regressions, and therefore only the plots relating to the first regression (with an AR lag) are reproduced in Figures 5.7 to 5.9. In line with the outcomes of the previous sub-section, the plot of the actual versus fitted values confirms that the fitted model only explains a minor portion of the variation in Nifty log returns. Despite this, few of the residuals are statistically significant and the scaled residuals approximate a normal distribution.

Checks on the serial correlation of the error terms were also undertaken. In case of Regression 1 the serial correlation coefficient of the residual series was significant at the fourth, tenth, and twenty-third lag (95%, 95%, 99% confidence levels respectively). In case of Regression 2, only the serial correlation coefficient for the first lag was significant at the 95% level of confidence. Thus, the latter regression seems to perform better in capturing the volatility dependencies, even if it has a lower overall explanatory power.

Figure 5.7: Plot of Actual and Fitted Values (Regression 1)

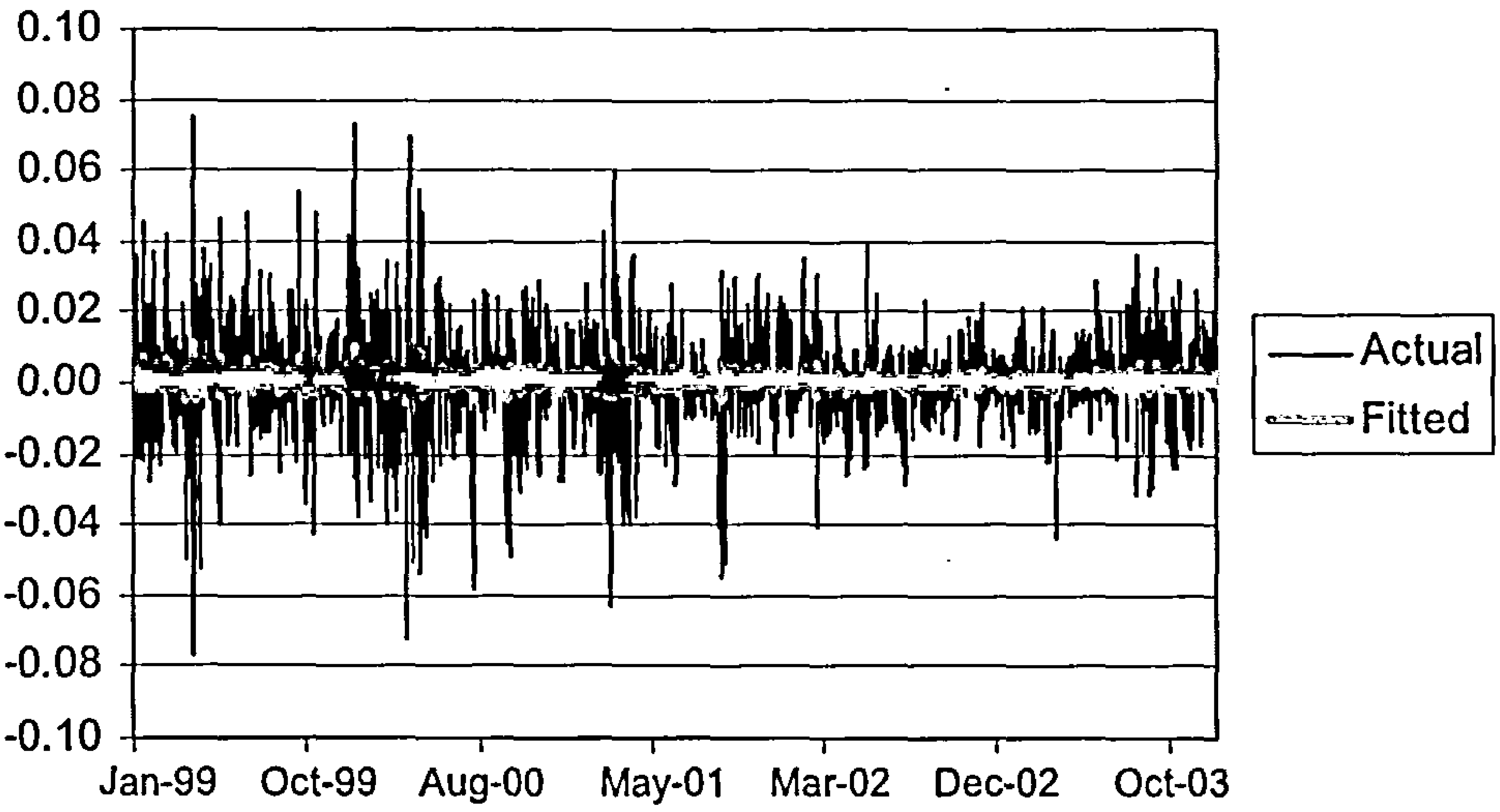


Figure 5.8: Plot of Transformed Residuals and Two Standard Error Bands (Regression 1)

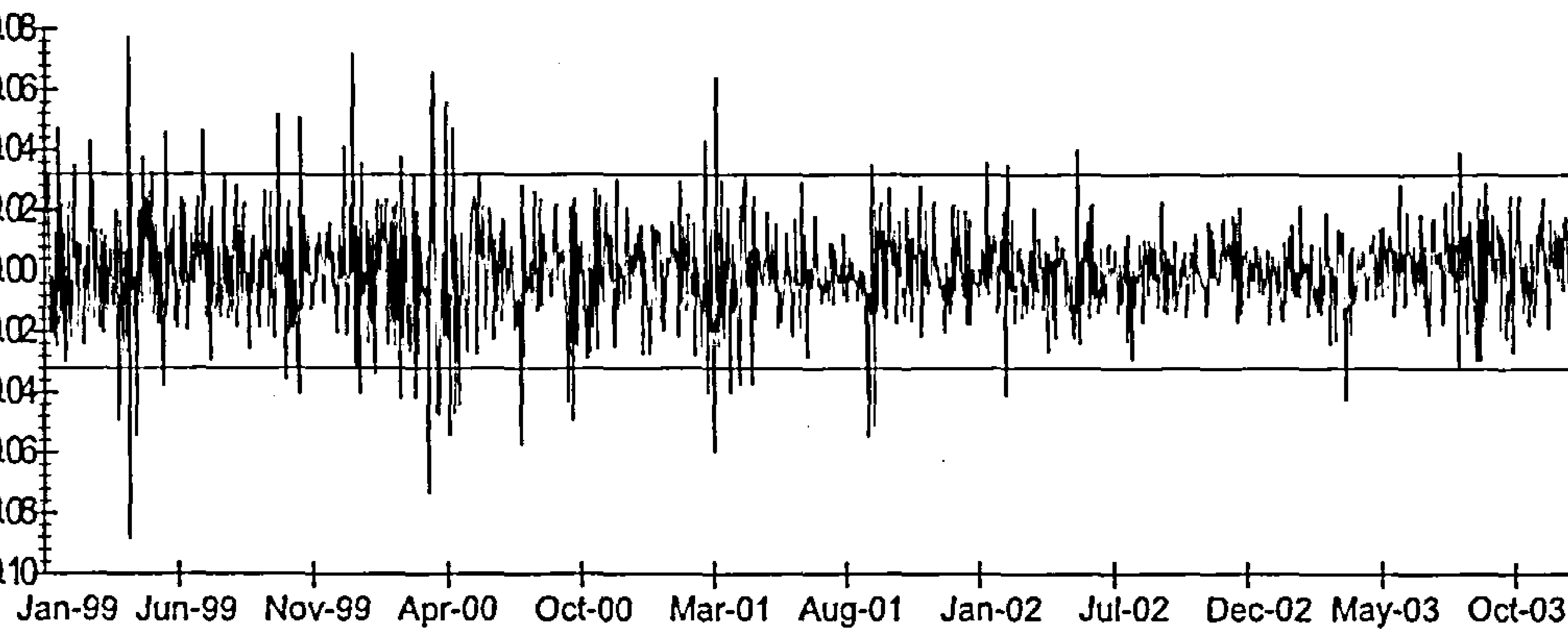
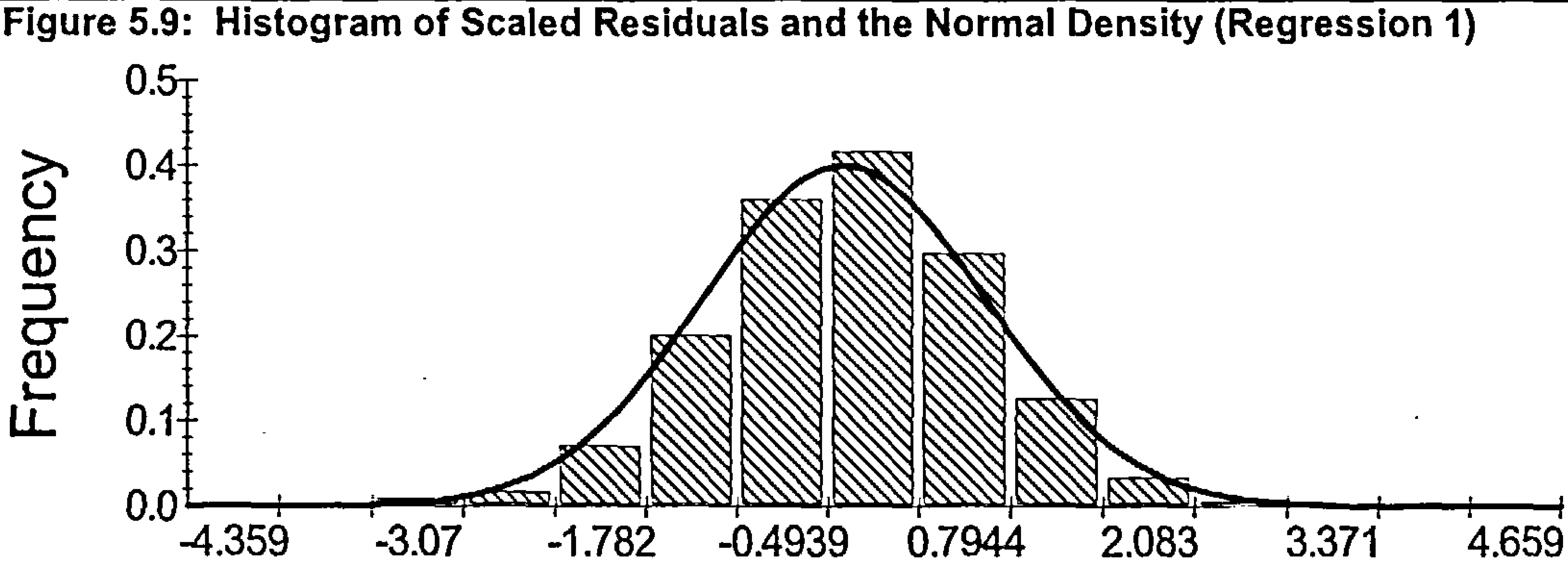


Figure 5.9: Histogram of Scaled Residuals and the Normal Density (Regression 1)



One possible reason for the absence of the risk-return relationship might be that a longer time series is required for the risk-return relationship to emerge more clearly, as discussed in

Section 5.3.3. Additionally, one cannot exclude the possibility that volatility is compensated for over longer term-periods – rather than on a daily basis. This makes it more difficult to detect the connection between volatility and returns using daily data since any relationship becomes "buried" in noise. This issue was investigated further by estimating an EGARCH-M model using monthly data. The first monthly closing observation for each of the months January 1999 till December 2003 was sampled, yielding a total of sixty (level) observations. Serial correlation coefficients for the monthly data were insignificant, except for the sixth lag which showed a coefficient of 0.42 and a t-ratio of 3.05. Checks for unit roots consisted of a series of ADF tests of different orders. Specifications with and without a trend yielded the same qualitative results. ADF(1) and ADF(3) tests rejected the null hypothesis of a unit root. The test-statistics for specifications without a trend were -4.57 and -3.60 as compared to a 95% critical value of -2.93. Despite this, ADF(6) and ADF(12) tests did not reject the null hypothesis of a unit root, where the test-statistics for specifications without a trend were -1.73 and -1.47 as compared to a 95% critical value of -2.93. [39]

LM heteroskedasticity tests as proposed by Engle (1982), together with the respective F-versions failed to reject the Null Hypothesis of no ARCH effects at the 95% level of confidence. Nonetheless the model estimation was proceeded with. The EGARCH-M model was specified in log returns as shown in Equation 5.13. The results as shown in Table 5.11, still confirm that the coefficient of h_t is not significant, re-affirming the absence of any relationship between returns and volatility.

Overall, the models estimated in this section unanimously suggest that Nifty volatility is not linked to returns, and therefore volatility may be excessive.

[39] In trying to avoid the use of data featuring a possible unit root, the log returns were differenced again. The null of a unit root was still not rejected for an order 12 test on the second difference of returns. When the series was differenced for a third time, GARCH models would not converge. The EGARCH-M model was thus estimated using the original log return series, given that this enables a more straightforward interpretation of results. Whilst the presence of a unit root may lead to spurious results, the bias usually materialises in high explanatory powers and highly significant coefficients. The results obtained when estimating the monthly data EGARCH-M model (Table 5.11) do not disclose such features, and thus any possible bias does not affect the main conclusion of the absence of a relationship between volatility and returns.

Table 5.11: EGARCH-M Model fitted to Nifty Monthly Log Return Data

Log Return Process:

Intercept: φ	Coeff: h_t	R {bar} ^{2}	F-Statistic: F (4,53)
0.0820	-12.0173	0.0409	0.5647
(0.94)	(0.81)	{-0.03151}	

Conditional Variance Equation:

Intercept: ω	Coeff: α_1	Coeff: γ_1	Coeff: β_1
-4.6262 **	0.1067	-0.3179	0.0926
(2.09)	(0.59)	(1.10)	(0.21)

The EGARCH-M was estimated through 58 monthly observations. T-ratios are shown in brackets underneath the respective coefficients. Significance at the 95% level of confidence is denoted by **. The Adjusted R^2 is shown in braces underneath the R^2 statistic.

5.8 Discussion

The former three empirical investigations may be used to comment on whether the Nifty Index volatility is justified or otherwise. This is an important question from a market microstructure point of view, since it relates to whether asset prices are subject to factors emanating from the market setup or traders' behaviour, as opposed to solely reflecting the underlying information. The standard methodology for making inferences on whether volatility may be deemed excessive is to analyse individual stocks and consider dividend expectations. Yet, this methodology cannot be readily applied to index data, given that indices do not directly yield dividends. In addition dividend data are inherently low frequency and thus not usually appropriate for market microstructure studies, where additional benefits may be reaped by using higher frequency observations. Therefore inferences are to be made by answering the questions of whether volatility is related to information flow patterns and whether it is related to returns.

Two types of tests were undertaken to inquire whether index volatility is related to the information flow. The first test considered day-of-the-week effects. It was found that index volatility varies (albeit not clearly significantly) during different days of the week – a Monday effect was detected in the index data. Whilst one may be tempted to attribute this to information accumulated over the weekend, this Monday effect was not present in individual stock data. This implies that the higher Monday volatility of the Nifty index is not information-related – and overall this test hints at traces of excessive volatility.

A second test considered monthly seasonality of volatility. It was found that volatility increases significantly during March and April and this may be attributed to the end-of-financial-year for a large number of Indian companies coinciding with the end of the Indian fiscal year. Despite this, whilst the April volatility was accompanied by equally significant increases in return magnitudes, the March volatility was not accompanied by comparatively significant increases in return magnitudes. This indicates that volatility during March might be more related to traders' conjectures about company performances, rather than official company news. It was also shown that volatility abates during the month of August – which may be attributed to a holiday effect. Whilst this may be due to a lower amount of news releases during August, it also casts doubts on whether the higher volatility observed during the other months may be excessive.

The issue of whether volatility is related to returns was investigated by EGARCH-M models which were fitted to index data sampled at daily and monthly frequencies. The models unanimously show that there is no significant relationship between volatility and returns – again hinting at excessive volatility.

What overall inference do these tests yield on Nifty volatility? Whilst the March-April jump in volatility may be partly justified by the end-of-financial year of quoted companies, we may still speak of excessive volatility components in the data. These include higher Monday volatility which cannot be explained by returns (and therefore information) in the underlying stocks, volatility during the month of March which is likely to be the response to guesses about company performance rather than official news, as well as the absence of a clear relation between volatility and returns. Thus one may assert that there is evidence of excessive volatility in the Nifty Index, which is likely to emanate from traders' behaviour or the market setup.

5.9 Conclusion

This study applied various empirical tests to identify volatility patterns on NSE, with a particular reference to how volatility may be related to information flow and returns. The latter aspects were emphasised in order to make inferences on whether the index volatility is justified or excessive – and this is an important issue in the field of market microstructure, since market designers often aim at curtailing unjustified volatility. This study used different volatility definitions and sampling frequencies, depending on the issue of interest. In line with numerous empirical papers including those cited in Section 5.2, typical volatility patterns were identified in the index data. These include volatility peaking during the opening of the day and then rising again at the end, as well as the presence of a Monday effect in Index data.

Tests revealed that Monday effects transpiring to some degree in index data, are more attributable to market microstructure factors such as index construction features or non-synchronous trading, since the Monday effect is not significant in the underlying stocks. NSE volatility tends to increase during the months of March and April, and this may be explained through an end-of-financial-year effect coinciding with the end of the Indian fiscal year. The increased NSE volatility during the month of March seems unjustified, since it is not accompanied by higher return magnitudes of similar statistical significance. The higher volatility during April is accompanied by a jump in returns of similar significance, and thus the pronounced April volatility seems related to information since the increased price dispersion during the trading day materialises in longer term returns. NSE volatility abates during August and this may be attributed to a holiday effect. Finally, EGARCH-M models show that longer-term volatility seems unrelated to the returns on NSE and this indicates that volatility may be excessive. Overall, these tests seem to point at unjustified volatility, perhaps with the exception of the higher volatility during April.

The findings were also rich in terms of providing important evidence regarding issues which have attracted considerable attention in the finance discipline, such as day-of-the-week effects. The investigation confirmed the finding of Madureira and Leal (2001), in that the Monday effect may appear in a stock index, but not in the underlying stocks. This shows the importance that researchers confirm the Monday effect through individual stock data rather than relying on index data. The finding is also relevant from the point of view of market designers, since the Monday effect in index data might be due to index construction features or non-synchronous trading. For instance, according to Campbell, Lo and MacKinlay (1997;

pp. 129) non-synchronous trading induces spurious serial correlation in index data, and this may also prevail when the index is comprehensively diversified. Given this, improving the index construction might not constitute a simple matter of further diversification of underlying stocks. Equal-weighted indices may also be liable to spurious serial correlation, and thus the weekly dependence in an index may not be immediately attributable to index weights emphasising less liquid stocks. The authors also noted that index serial correlation may arise when the underlying stock betas are of the same sign, or if the returns on individual stocks have small means. This may present a possible trade-off on part of market designers; whilst they may opt to minimise serial dependence by avoiding the former features, the selection of stocks to be included in an index should primarily be influenced by the objective of achieving a comprehensive yardstick relating to the particular market or economy. The task of selecting the underlying stocks might prove even more challenging when constructing an index to represent a particular economic sub-sector – where the betas and the returns of the selected stocks are likely to be similar. Campbell, Lo and MacKinlay (1997; pp. 99) also stated that it is unlikely that the weekly serial correlation prevailing on actual markets may be exclusively attributable to non-synchronous trading. This implies that minimising such dependencies might require a completely different track than the possibilities outlined above.

This investigation also provided important evidence as regards the January effect often observed on other markets. A monthly effect on NSE was observed during the months of March and April rather than January, and this implies that it is likely that this effect is related to the end-of-financial-year of listed companies and/or the end of the fiscal year. There is no evidence of significant excess returns on NSE during the month of January. This contrasts with the empirical evidence presented by Clare, Psaradakis and Thomas (1995), who noted both a January effect and April seasonality around the fiscal year end, in the context of the UK equity markets.

One main innovation of this analysis relates to the interpretation of different models – in particular the relevance of commonly-used methodologies to the assessment of whether volatility is justified or excessive. Given the profound relevance of this issue for market microstructure, the latter discipline would benefit from additional methodologies which may be applied in answering such questions, in the absence of data about dividend expectations.

The empirical results also show that further research is required as to why index data tend to feature a Monday effect and why this might not always be confirmed when analysing the underlying stocks. The main explanation for Monday effects so far has been the accumulation of news during the weekend; but if this is indeed the case the Monday effect should show up in individual stock data as well. Similarly, other empirical studies of securities markets where the quoted companies do not end their financial years in December, would be useful in assessing whether January effects are mainly caused by end-of-financial-year company results and/or the end of the fiscal year.

Finally, the discovered volatility seasonality patterns are of relevance to the analysis of changes in volatility following a call auction suspension on NSE. This topic is investigated in the subsequent two chapters.

APPENDIX 5.1

A Summary of the Intra-Day Data Sets

Before Call Auction Suspension			After Call Auction Suspension	
Tuesday	18 May '99	1	Wednesday	9 June '99
Wednesday	19 May '99	2	Thursday	10 June '99
Thursday	20 May '99	3	Friday	11 June '99
Monday	24 May '99	4	Monday	14 June '99
Tuesday	25 May '99	5	Tuesday	15 June '99
Wednesday	26 May '99	6	Wednesday	16 June '99
Thursday	27 May '99	7	Thursday	17 June '99
Friday	28 May '99	8	Friday	18 June '99
Monday	31 May '99	9	Monday	21 June '99
Tuesday	1 June '99	10	Tuesday	22 June '99
Wednesday	2 June '99	11	Wednesday	23 June '99
Thursday	3 June '99	12	Thursday	24 June '99
Friday	4 June '99	13	Friday	25 June '99
Monday	7 June '99	14	Tuesday	29 June '99
Tuesday	8 June '99	15	Wednesday	30 June '99

The sets include 15 days where a call auction was used to open and close the trading session, and a further 15 trading days following the call auctions suspension. The Nifty Index returns for each trading day were sampled at one-minute intervals.

CHAPTER 6:

THE IMPACT OF THE SUSPENSION OF OPENING AND CLOSING CALL AUCTIONS ON NSE

6.1 Introduction

The design of trading protocols and the evaluation of their effectiveness are two of the most important topics in market microstructure. As outlined by Madhavan (2000), trading protocols provide the framework within which markets operate and thus play a central role in price formation. This implies that evaluating the effectiveness of different protocols is a main concern of market authorities, regulators and market participants.

One issue which has attracted much attention in this area relates to the effectiveness of call auctions as compared to continuous trading systems or hybrid structures featuring both processes. Given that call auctions batch a number of trades in a given security at a particular point in time, they should theoretically provide an efficient mechanism for aggregating diverse information because trading does not take place until price discovery has occurred (Economides and Schwartz; 1995). This contrasts with a continuous trading setup where price discovery and trading take place simultaneously implying that trades may occur at "false" prices, as noted by Schwartz (2000). However, continuous trading usually involves greater immediacy and therefore less price risk than an auction. In particular, given that there is a delay in establishing the trading price during an auction, the "true" price may change between the submission and execution of an order, as noted by Madhavan (1992). Economides and Schwartz (1995) thus argued that a hybrid system is best: an opening call auction to efficiently aggregate overnight information, followed by continuous trading during the day. This view has prompted many of the major exchanges to introduce an auction to open and in some cases to close the day's trading, as outlined by Ellul, Shin and Tonks (2004).

The balance of empirical evidence on call auctions is inconclusive, with some studies identifying gains from the auction process but others finding that continuous trading is superior. These inconsistencies may be due to the fact that call auctions vary in structure, and that they are typically applied in the context of different trading protocols. As noted by Madhavan (2000), empirical comparisons between call auctions and continuous trading are often hindered by the fact that the two systems being compared rarely share a common set of trading protocols. Similarly, in looking at the impact of replacing call auctions by continuous trading, researchers often have to deal with the fact that such changes are typically accompanied by other reforms which make it difficult to conclude if costs or benefits are due to the switch to continuous trading or to other factors.

A further limitation of the existing empirical literature on call auctions is that it is mostly concerned with the stock markets of the major industrial countries. Exceptionally, Shastri, Shastri and Sirodom (1995) investigated the impact of the opening call auction on the Bangkok Stock Exchange, and found that prices at the opening call were more volatile than during the rest of the day, although this could be because uncertainty and volatility tend to peak at the start of the trading day following the overnight closing. In general there has been little research on stock exchanges in emerging markets. This is an important omission given that emerging stock markets tend to be less liquid than those of developed countries, and it has been argued that call auctions are particularly suited for trading less liquid stocks (Madhavan, 1992). This suggests that in emerging markets call auctions may have advantages over continuous trading systems in fostering the efficient trading of relatively illiquid securities. However, this argument also underlines a further difficulty in comparing call auctions and continuous trading: if the effectiveness of an auction depends on the liquidity of the market, a proper comparison must control for variations in market liquidity and other factors.

This investigation adopts a novel approach in analysing the effectiveness of call auctions, in that it considers the impact of the suspension of opening and closing call auctions by NSE on the 9th June 1999.[40] This change in trading procedures related to one of a series of "experiments" whereby NSE was endeavouring to introduce call auctions to an otherwise continuous trading setting. This is probably the first study of the impacts of such a suspension, and an inherent strength of this empirical setting is that other market protocols and arrangements remained unchanged. Furthermore, since the continuous trading session took place both before and after the suspension, it is unlikely that the auctions would have limited the degree of immediacy in the market.[41] Thus, this is *not* a comparison between two systems with several different trading protocols. This enhances the robustness of the conclusions, in that any changes following the suspension are more likely to be the result of the change concerning the call auction. Being an emerging market exchange, NSE features a significant

[40] The NSE circular announcing this change was issued on the same day.
[41] Upon the suspension of the call auction on NSE, the time devoted to continuous trading was unchanged.

proportion of less liquid securities, and this enables the investigation of any differences in the impacts concerning more and less liquid securities in the market.[42]

This chapter has two main objectives. The first one is to estimate the impact of the suspension of call auctions at the NSE, using the standard procedure of comparing the volatility, efficiency and liquidity (VEL) of traded securities in the market before and after suspension (Amihud, *et. al.*, 1997). The second aim is to infer the value of the call auctions to traders using an event study to calculate the cumulative abnormal returns (CARs) for the sampled securities. If the auctions improved the price discovery process, one may expect a deterioration in VEL following suspension and negative CARs. If on the other hand, the auctions led to reduced immediacy and increased price risk then one may expect improvements in VEL following suspension, together with positive CARs.

The tests undertaken in the analysis suggest that VEL broadly improved after the suspension of the auctions, but the mean CARs were generally negative. Thus, further tests are conducted to examine the relationships between the responses to the auction suspension and the composition of the sampled securities, particularly in respect of their liquidity. It turns out that stock liquidity is an important factor in explaining the former results, a finding which is also consistent with the arguments of Ellul, Shin and Tonks (2004).

The objectives of this investigation should be qualified in that it seeks to infer the effectiveness of call auctions from the point of view of the market in general; yet one should note that a feature which is desirable from the point of view of most market participants might not prove as desirable to specific players, and *vice versa*. In this setting, the auctions might have presented particular advantages or disadvantages to specific market participants, however this analysis abstracts from these issues and focuses on the reaction to suspension on part of the general market; the desirability of call auctions to specific trader categories may be explored in future research.

The rest of the chapter is structured as follows:

A review of the existing literature relating to call auctions is shown in Section 6.2. Section 6.3 discusses the possible findings and the data set. The subsequent sections focus on VEL

[42] Ellul, Shin and Tonks (2004) identify a similarly clear-cut comparison between the opening and closing calls on the London Stock Exchange and the parallel off-exchange dealer market. However, results for developed markets may not be applicable in an emerging market.

changes. In particular Section 6.4 investigates the impacts of the suspension of call auctions on volatility, Section 6.5 tackles the impacts of suspension on efficiency and Section 6.6 deals with liquidity changes. Each section offers a description of the adopted methodologies given that different tests are undertaken for assessing the changes for each of these factors.

Section 6.7 traces the traders' reactions to the call auctions suspension through an event study. The Cumulative Abnormal Returns (CARs) pattern which is obtained, although robust and significant, seems inconclusive at first sight. In Section 6.8, further tests are undertaken in order to infer whether the latter ambiguity may be explained by accounting for the initial *betas* or the liquidity of the sampled stocks. Section 6.9 offers various possible explanations for the observed empirical results, whilst Section 6.10 concludes.

6.2 Review of Relevant Literature

Trading systems may either rely exclusively on call auctions or continuous trading, or else the protocol may provide for a hybrid system. For instance the trading sessions of NYSE commence and close with a call auction, whilst a continuous trading session is held in between. Exchanges which (at the time of writing) match orders exclusively through call auctions include Bursa Malaysia (the former Kuala Lampur Stock Exchange) which holds periodic call auctions for each of the traded securities. In the latter exchange, the interval between call auctions may differ across stocks and it ranges between one second and 99 seconds.[43]

Call auctions vary in structure as outlined by Economides and Schwartz (1995) and different call auction structures may have different effects on trading activity.[44] This may partly explain the mixed evidence on call auction efficacy as outlined below. Furthermore, different markets have different trading protocols and it may be that similarly-structured auctions have different implications across markets.

The central issue in the debate between call auctions and continuous trading is the trade-off between information efficiency and immediacy. A sequence of call auctions aggregates

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[43] http://www.bursamalaysia.com/website/trading/matching.htm (accessed 7th May 2004).
[44] For instance Roth and Ockenfels (2002) presented evidence that subtle differences in internet auctions used for trading non-financial assets can cause pronounced differences in bidding behaviour.

information more efficiently, especially where asymmetric information is a problem and dealers are reluctant to take the opposite side of trades. However, periodic auctions lack continuity and therefore reduce the immediacy of trading. They may also result in higher information costs given that current prices are available less frequently as outlined by Madhavan (1992). However, the latter arguments are less relevant where call auctions are used at the opening or closing, since trading still occurs continuously for the rest of the day. Moreover, lack of immediacy is an issue in any setting in which trades are clustered in a short period, and this may occur independently of an auction. For instance, Admati and Pfeliderer (1988) gave a theoretical account in which the transactions of uninformed traders are bunched in the lowest cost period. Similarly, traders who submit orders prior to the market opening have to wait for execution until the opening, irrespective of the protocols used at opening. Thus, it can be argued that an opening call auction, such as we analyse for the NSE, is unlikely to have much effect on immediacy.

The literature background now proceeds with an account of theoretical, empirical and experimental studies in Sections 6.2.1 to 6.2.5.

6.2.1 Theoretical Literature

Various authors such as Economides and Schwartz (1995) argued that call auctions aggregate different expectations of market participants thereby increasing price discovery and pricing efficiency. Schwartz (2000) contrasted this notion to a continuous market setting where prices are discovered whilst trading occurs, whereas a call market executes trades after the price discovery occurs. In the theoretical model of Hillion and Suominen (2004), closing call auctions are successful in reducing the potential for market participants to manipulate closing prices.

Madhavan (1992) theoretically investigated the performance of different market structures and concluded that auctions aggregate information more efficiently, especially when the level of asymmetric information on the market is high, and dealers become reluctant to take the opposite sides of trades. On the other hand, the lack of continuity of a periodic auction may result in higher information costs given that current prices are available less frequently. Yet, the latter argument might not be applicable to those market settings where auctions are solely used at the opening and at the closing, since trading still occurs continuously for the rest of the day. In addition if call auctions are successively held at close enough intervals (e.g. Bursa Malaysia) the loss of continuous price indications may not be as pronounced.

A second disadvantage of call auctions is that some market participants may use the setup to conceal information from other traders. For instance, in the model of Caillaud and Mezzetti (2004) some participants give up profitable trading opportunities in an initial auction, in the hope that the resulting price movements materialise in higher subsequent profits.

The learning process on call auction markets was investigated by Pouget (2004 a), through a comparison with a Walrasian setup. In the latter system, tentative prices are announced and adjusted, until a price is set where demand equals supply and the trades occur at the latter price. If traders learn through a belief-based model (where previously *not chosen* actions are more likely to be chosen) equilibrium is discovered in both setups. Yet, when traders learn through a reinforcement-based model (where previously *chosen* actions are more likely to be chosen) equilibrium is discovered in the Walrasian setup, but not necessarily in the call auction. In the latter case, if informed traders do not disclose the equilibrium price at the outset, the uninformed traders do not choose the equilibrium price either since they follow reinforcement-based learning. The Walrasian setup is better since it does not induce price uncertainty, as is the case in a call auction. The author suggests that organising a pre-opening period prior to the auction, may help in making the process resemble more closely a Walrasian setup.

Another disadvantage of call auctions as outlined by Madhavan (1992) is that the underlying stock price may change during the time from which the trader submits his order till when the order is executed. Yet, these drawbacks are common to those situations when trades cluster to one specific point or short period and such outcome may occur independently of an auction. For instance, in the theoretical model of Admati and Pfeliderer (1988), uninformed traders choose to transact in the lowest cost period. In addition this disadvantage is "immaterial" in opening call auctions, since traders who submit orders prior to the opening of a continuous market still have to wait till execution, facing the same underlying risk of a change in the fundamental value of the stock.

Finally, one may argue that call auctions undermine prompt access to the market, given that orders cannot typically trade instantly, but have to wait till the next auction. Yet, one should also consider that most traders might not demand instantaneous liquidity and are at times prepared – or willing – to postpone their trading to a specific point. The theoretical findings of Admati and Pfeliderer (1988) and Vayanos (1999) corroborate this argument.

6.2.2 Empirical Comparisons Between Call Auctions and Continuous Trading

Various studies have empirically investigated the inherent pricing efficiency of call auctions as postulated by the former theoretical arguments. An investigation of the learning process of traders during the pre-open call auction of the (former) Paris Bourse is found in Biais, Hillion and Spatt (1999). The authors noted that the price discovery process reaches its peak at the last minutes of the call, whereas orders posted during the initial minutes may be classified as "noise". The latter may be consistent with traders not being aware of the fundamental value of the security, or with buyers (sellers) submitting orders at artificially low (high) prices in an attempt to drive the price in a favourable direction.[45]

Amihud and Mendelson (1987) empirically compared the opening call auction and the continuous trading session on NYSE, in terms of the stock return distributions, the convergence of prices to fundamental values and serial correlation patterns. The authors used a time series model, to distinguish between the fundamental values of securities as opposed to the actual prices. They concluded that opening returns exhibit greater dispersion and show higher negative autocorrelation patterns than closing returns. The authors also noted that the error term of their model, was greater for the opening prices, as compared to the closing ones. Similarly, Shastri, Shastri and Sirodom (1995) found that opening prices on the Thailand Stock Exchange, which are determined through a call auction, tend to be more volatile than those of the rest of the day. While this may be taken as an indication against the pricing efficiency of call auctions, one should not overlook the fact that uncertainty is typically at its peak during the opening of a trading session, following the overnight market closure. Thus, these empirical results may emanate from the initial uncertainty, rather than any inherent inefficiency of auctions. According to Biais, Glosten and Spatt (2002), the latter argument was confirmed by the studies of Amihud, Mendelson and Murgia (1990) and Amihud and Mendelson (1991), who empirically analysed call auctions which were not held at the start of

[45] This contrasts with the findings of Davies (2003) and Dia and Pouget (2004a), that most of the orders at the pre-opening period of the Toronto Stock Exchange and the West-African Bourse are submitted with the intention of trading.

the trading day. The latter studies found that auction markets are not inherently less efficient than continuous trading.

Ellul, Shin and Tonks (2004), found that price discovery tends to be higher during the London Stock Exchange call auctions as compared to the contemporaneous dealership market transactions taking place off the exchange. Contradictory results were obtained by Angel and Wu (2001) who evaluated the possible introduction of an opening call auction on Nasdaq by simulating an auction using existing Nasdaq data. The authors found that the introduction of an opening call auction might lead to lower price discovery.

As regards volatility of call auction pricing, Angel and Wu (2001) noted that dealers may be better equipped to handle the random nature of order imbalances, as compared to call auctions. Yet, the main arguments of this study rely on a comparison between dealers and auctions – rather than an assessment of call auctions on their own. Indeed, the authors did not rule out the presence of a call auction in improving the opening procedures on Nasdaq.[46] Thus, in applying this reasoning to NSE, one should note that given the absence of market makers, call auctions may still be a positive feature on this exchange.

Call auctions increase liquidity by batching a number of transactions which might have otherwise been executed sequentially, as discussed by Economides and Schwartz (1995). This implies that auctions should reduce trading costs. Kehr, Krahnen and Theissen (2001) empirically examined the difference in trading costs between call auction and continuous trading sessions on the Frankfurt Stock Exchange. They found that the call auction provides transaction cost savings for small transactions, but not for large transactions, which are cheaper to execute in the continuous session. Similarly, Ellul, Shin and Tonks (2004) when comparing call auction trading to dealership trading on the London Stock Exchange, found that small orders tend to be cheaper to execute in the call auction, whereas larger orders tend to be cheaper to execute in the dealership market. Yet, according to the empirical evidence found by the latter authors, the system which results in lower overall costs tends to vary with the trading volume.

Comerton-Forde (1999) investigated stock return data from the Australian Stock Exchange and the Jakarta Stock Exchange. The former exchange commences with a call auction, while

[46] The authors concluded that "What is needed is a hybrid mechanism that incorporates the best features of a call market with the advantages of the existing market" (i.e. dealers). Schwartz (2000) advocated the introduction of a call auction on Nasdaq, as well as on other US markets.

the latter one commences with continuous trading. The author concluded that the call auction increases liquidity and reduces volatility, at the initial phases of the trading sessions. Such benefits are more pronounced for less liquid stocks. Despite this, one should note that such studies where comparisons are undertaken across different exchanges tend to be hindered by the fact that the two systems being compared rarely share a common set of trading protocols, as discussed by Madhavan (2000).

The issue of whether call auctions constitute a better trading method for less liquid stocks has also been debated. Various authors such as Barry and Brown (1984) have associated a higher level of asymmetric information with smaller stocks. This implies that call auctions are especially suitable for trading smaller stocks, given that according to Madhavan (1992) call auctions perform particularly well when the level of asymmetric information is high. Despite this, Ellul, Shin and Tonks (2004) found that on the London Stock Exchange, where trading at the opening and at the closing may take place both through call auctions and through the dealership system, less liquid stocks tend to trade in the latter market more frequently, even if the call auctions offer cost savings and higher pricing efficiency. One possible explanation for this behaviour is that dealers' services add a value to the market structure given that they guarantee the availability of a counterparty during most of the time, whereas call auctions may depend to a higher degree on public orders. This creates a "thick market externality": traders will only enter an auction if they believe sufficient traders will be present so as to establish an informationally-efficient price. Despite this, the latter argument might not be directly applicable to the investigation at hand, given the absence of dealers on NSE.

6.2.3 Empirical Studies of Conversions between Systems

The efficacy of call auctions and continuous trading has also been compared, by considering those cases where exchanges switched in between systems. Again, one should interpret these studies with care, since as noted by Amihud, Mendelson and Lauterbach (1997), such changes typically involve other reforms to the trading system making it difficult to conclude if costs or benefits are due to changes in the call auction trading or to other factors.

Muscarella and Piwowar (2001) using event study methodology found that on the former Paris Bourse the stocks which were transferred to continuous trading experienced positive abnormal returns, whilst those transferred to call trading showed negative abnormal returns. Similar results in favour of continuous trading methods were found by Amihud, Mendelson and Lauterbach (1997) and Lauterbach and Ungar (1997), both studies focusing on the Tel Aviv Stock Exchange. Henke and Lauterbach (2005), presented analogous results in respect of stocks traded on the Warsaw Stock Exchange. Yet, one should note these types of results do not necessarily imply that call auctions are inherently inferior trading systems since they may reflect investors' preferences for stocks that trade continuously. This was confirmed by Kalay, Wei and Wohl (2002) who observed increased trading volumes for Tel Aviv Stock Exchange securities which moved to continuous trading, and reduced volumes for those stocks which remained trading through the call auctions.

Aitken, Comerton-Forde and Frino (2002) analysed the introduction of a closing call auction on the Australian Stock Exchange, and noted that on high-volatility days, there is a pronounced tendency for traders to delay their trading till the auction. They suggested that call auctions are more highly valued by traders on high-volatility days. Despite this, one may question whether this effect might constitute a general tendency to postpone trading on high volatility days (in the hope that volatility reverts back to normal levels), irrespective of whether the session closes off with an auction or otherwise.

The changes in VEL factors of stocks when the latter switch from call auctions to continuous trading might also depend on the initial liquidity levels of the stocks. For instance, Kairys, Kruza, and Kumpins (2000a) found that when the Riga Stock Exchange shifted from a call auction to a continuous trading system the overall liquidity impact was positive, yet the benefits accrued to stocks which were already liquid whilst the volumes of smaller company stocks declined.

6.2.4 Other Empirical Studies

Ronen (1998) studied the impact of trading mechanisms on volatility by considering a change in the trading procedures on the Tel-Aviv Stock Exchange. The exchange used a call auction to end the trading day; yet in 1988 the mechanisms were reversed whereby the call auction was held prior to the continuous trading session. The author reported no significant differences in opening volatility following the change, concluding that the trading mechanism does not affect the opening volatility.

Comerton-Forde and Rydge (2006 a) considered two empirical cases of manipulative orders: the first one for a liquid stock and the second one for an illiquid stock. They studied how auctions featuring different matching algorithms perform in dealing with market manipulation. The authors showed that manipulative orders can impact on the prices established in the auction and manipulation is less costly in illiquid stocks. In the case of the illiquid stock, a price was established in the presence of a manipulative order – yet the auction did not establish a price when the manipulative order was eliminated. This casts doubts on the notion that auctions are particularly suited to trade less liquid stocks. This idea corroborates with the empirical findings of Madhavan and Panchapagesan (2000) who analysed the opening auction on NYSE. The authors found that call auctions might not be the ideal trading setup for less liquid stocks, given that the latter are considerably sensitive to order imbalances which might result in mispricings.

With reference to the possible differences in auction algorithms, Comerton-Forde and Rydge (2006 a) noted that when only the first criterion in the algorithm is used to set the price, different algorithms tend to establish the same price (since most algorithms start with the basic rule of maximising trading volume). Yet, when the subsequent criteria have to be considered in establishing the auction price, algorithms tend to establish different prices – since the subsequent criteria may differ across algorithms. The authors argued that the auction algorithm on its own might be unable to restrain the effects of manipulative orders and complementary features may thus be required. The latter may include order restrictions, market surveillance and implementing a random call auction termination time, since manipulators typically submit orders just before termination, so that other traders might not have sufficient chance to respond. Volatility extensions may potentially curb market manipulation; the pre-open time is extended when the stock price deviates considerably from a reference price, since this might indicate the presence of a manipulative order. In this way, balancing liquidity may be attracted on the opposite side of the book.

Comerton-Forde and Rydge (2006 b) studied the changes on the Australian Stock Exchange following increased auction transparency measures and modifications to the call auction algorithm. The measures intended to enhance transparency included restrictions on undisclosed orders and an extension of the pre-close period (where orders are displayed to the market without any trading taking place). The change in the auction algorithm involved the introduction of the basic principle that the established price maximises the trading volume (thus making the algorithm similar to the one adopted by NSE). The authors reported increased efficiency and trading volumes following these changes, and they noted that these benefits extended to the less liquid stocks trading on the exchange.

6.2.5 Experimental Studies

In an experimental investigation, Theissen (2000) concluded that call auctions present benefits in terms of higher pricing efficiency and lower trading costs. A previous experimental study was conducted by Schnitzlein (1996) who found that whilst prices converge to their true levels in both call auction and continuous trading settings, uninformed traders incur lower adverse selection costs when they trade in a call market.

Biais and Pouget (2000) considered market settings involving call auctions to different degrees. Their findings suggest that call auctions on their own might not be the ideal price discovery tool. A better alternative might be to organise a pre-opening period prior to the auction, where a volume maximising price is based on the incoming orders. The latter price is disseminated, yet no trades are executed. According to the authors, the pre-opening information augments price discovery in the subsequent call auction period and the continuous trading session.[47]

Pouget (2004 b) considered the convergence towards equilibrium prices in a call auction market as compared to a Walrasian setup. The author concluded that the Walrasian setup features less frequent deviations from equilibrium and it can generate higher volumes, since uninformed traders may refrain from participating in the auction.

6.3 Expected Results and Data

6.3.1 Expected Results

Overall, the theoretical and empirical research on call auctions has not yet materialised in clear-cut conclusions, and this may be partly attributable to the fact that call auctions vary in

[47] A theoretical model of the role of pre-opening periods in securities markets is found in Dia and Pouget (2004b). The authors found that pre-opening periods have a positive role in enhancing liquidity and information dissemination.

structure and they may have different impacts across markets. For instance Kairys, Kruza and Kumpins (2000b) suggested that the actual effects of changes in trading systems may vary, given that different exchanges adopt different listing requirements, price limits, and minimum tick sizes. Heterogeneous results may also be due to the differing thickness of the markets. This complicates the formulation of the hypotheses to be tested by researchers.

This analysis has two main objectives. The first one is the assessment of the impact of the auction suspension on the volatility, efficiency and liquidity (VEL) of traded securities on NSE. As described in the previous section, existing literature suggests that the presence or otherwise of call auctions may impact on VEL. Call auctions may affect volatility if their information dissemination process impacts on the proportion of uninformed investors or changes the potential for market manipulation. Auctions may affect pricing efficiency due to potentially enhanced information aggregation, whereby trading only occurs after observing a set of submitted orders. The liquidity impact of call auctions may result from changes in traders' willingness to transact due to changes in the fairness of the matching system and the speed of execution.

Whilst volatility, liquidity and efficiency may be thought of as distinct items, one should not sideline the likely interconnections between them. For instance, if the presence of a call auction leads to increased (decreased) pricing efficiency, then it should also lead to decreased (increased) volatility due to lower (higher) deviations from the fundamental values of securities. Similarly, changes in efficiency should lead to changes in the fairness of transactions; this would impact on the willingness to trade, resulting in liquidity changes. Liquidity changes may also lead to changes in volatility, for instance if the higher number of transactions leads to enhanced price discovery. In addition, one may also speak of liquidity externalities in the sense that liquidity changes for a particular security may impact on the liquidity of other securities (Amihud, Mendelson and Lauterbach; 1997). This chapter does not address the former interrelationships across the separate VEL factors, since the VEL analysis is intended to gauge the *net* changes in volatility, efficiency and liquidity. These changes might not emerge if the researcher were simply to focus on traders' immediate reactions to the auction suspension. Overall, the reader should keep in mind that VEL encompasses three separate (interrelated) variables, even if occasionally it might be referred to as a single factor in the text for the sake of brevity.

The second aim of the chapter is to infer the value of the call auctions to market participants through an event study. If the auctions assisted in price discovery, one may expect deteriorations in VEL following suspension. In addition, the suspension of the auctions should be value-decreasing, resulting in negative CARs. Such a result would be in line with the findings of Pagano and Schwartz (2003) that the introduction of a closing call auction at the Paris Bourse created improvements in the price discovery process, without any negative effects during the continuous trading session. If on the other hand, the auctions led to reduced immediacy and increased price risk then one may expect an improvement in VEL following suspension, together with positive CARs. This would corroborate the arguments of Ellul, Shin and Tonks (2004) that the value of call auctions may be limited by "thick market externalities" by which traders only enter the auction if they believe that a sufficient number of other traders will be present so as to establish informationally-efficient prices.

In considering which of the former two outcomes may be more likely, it is essential to hypothesise an argument which (attempts to) explain the above mixed evidence. One consideration which might solve the "puzzle" is that *ceteris paribus*, traders tend to prefer stocks that trade continuously rather than through sequential call auctions since the former setup permits instant access to the markets. Yet, when call auctions are used in conjunction with continuous trading, say at the start and at the end of a continuous session, they do not limit the immediate access to the market given that the stocks still trade continuously for most of the time. In such cases, auctions might be considered as "positive" by market participants, given that they help in the price discovery process without prohibiting the security from continuous trading. One study which supports this argument was conducted by Pagano and Schwartz (2003). The authors used the market model R^2 statistic to investigate the impact of the introduction of a closing call auction at the (former) Paris Bourse. They found that the closing call led to improvements in the price discovery process, without any negative liquidity effects during the continuous trading session.

As regards this empirical study, NSE followed a system where the continuous trading session was preceded and followed by a call auction. These auctions were discontinued on 9th June 1999. Following the above reasoning, one may expect stock prices to show negative CARs, on the grounds that these auctions were previously serving to integrate different market expectations and thus establishing more efficient prices, without hindering immediate access to the market during the day. If these expectations are correct, one may also expect deteriorations in VEL. Despite this, in view of the mixed evidence presented in the former section, one cannot exclude the possibility of obtaining diverse results.

6.3.2 Data and Notation

NSE began with continuous, screen-based, nationwide electronic trading and subsequently introduced a pre-opening and post-closing call auction on an experimental basis. For the rest of the trading day the system functioned as a continuous pure limit order book market, with time and price priorities applied to incoming orders. A note about the actual procedures governing the auction is warranted. This description is based on information obtained from NSE circulars and intra-day data files. Whilst further details about the auction would have been desirable, no responses were forthcoming to requests for information from NSE.

The transaction data files did not explicitly distinguish between trades which were executed during the call auctions from the trades executed during the continuous session. However, when the opening and closing call auctions were held, the initial and closing part of the trading was characterised by trades occurring in successive stocks in an alphabetical order. For instance, trading typically began with the stock designated with a code ABB or ACC and a number of trades in the particular stock were executed at a single price. The alphabetical sequence typically went on up to the stock designated by ZEETELE. Trading during the rest of the day seemed to occur randomly across stocks in no particular order. This suggests that the system executed an auction for each stock in an alphabetical sequence (and the auction process was not subsequently repeated). Following the opening auction for each stock, the system switched to continuous trading. Similarly, following the closing auction for each stock, trading stopped for the rest of the day.

One further feature which permitted the distinction between the auction and the continuous session was the typical break in between the regimes. Whilst technically there was no trading break intended between the opening auction and the continuous session, a typical 10 second break was noted when inspecting the data files. Such break was not typically observable during the rest of the trading day, where it is reasonable to expect at least three transactions during any particular second. The termination of the continuous trading session and the start of the closing auction is clearly distinguishable by an intended trading halt of around 20 minutes. Brokers could submit and cancel orders during this break and it is reasonable to assume that brokers had access to a limited range of orders on both sides of the book during this interval.

Not all stocks trade during the opening and closing auctions, presumably due to insufficient demand or supply at price schedules which permit trading. When a stock does not trade during the auction, this is not specifically indicated in the data files, and therefore in order to obtain an idea of stocks which did not trade during the auction, one would have to start with the whole list of stocks and eliminate the stocks which trade during the auction.

One should note that whilst the exchange specified formal timings during which trading occurred, this was not followed unfailingly during the trading days. For instance, the trading process at times started at 9:55, when the designated starting time was 9:45. Similarly, whilst there was a designated time for the switch from the call auction to continuous trading, the switch mainly occurred upon termination of the alphabetical auction process described above. The continuous trading session's formal halt was intended to occur at 15:30, and this yardstick was usually upheld, take or leave around two seconds either way. The closing auction was subsequently held, following a trading break of around 20 minutes. The trading day stopped upon the termination of the closing auction across stocks; this usually lasted around three minutes as shown in Table 6.1.

Following the auction suspension on 9th June 1999, a circular issued by NSE on the 15th June 1999 speaks of the implementation of a proposed pre-open procedure. This terminology requires some clarification. A pre-open period does not imply a call auction; for instance authors such as Dia and Pouget (2004 b) use this term to describe a process where traders may submit orders and tentative prices are disseminated – yet no transactions actually take place. The main idea behind this process would be to glean information about traders' expectations following the overnight break. Yet, the former NSE circular mentions that this pre-open period, establishes prices in such a way to match the largest number of traded quantity of securities. For instance the circular specified: "To the extent possible the opening price is determined at one of the observed price points in the market and is a single price at which all opening trades take place". In this way, one may assume that the term pre-open period on NSE is referring to a process where the first trading price for a security is established. Yet, a look at the data files discloses that this pre-open period functioned in a different way from an auction. This is inferred by looking at successive trades in the same stock, taking place during the same second. One notes that such trades in the same stock were executed at different prices – whereas in a call auction these trades should occur at the same price. This confirms that when NSE suspended the auction on 9th June 1999, the exchange only re-adopted it on the 17th November 1999 to suspend it again on the following day.

No material details were available as regards the algorithm of the auction setup considered in these chapters. However, the above-mentioned circular described a new pre-open algorithm and compared it to the previous one; this may offer indirect information about the auction setup of interest, since the circular specifies the differences as between the algorithms. It seems that in both setups the NSE pre-open algorithm followed the basic rule that the opening price maximises the total traded quantity. Presumably, this procedure also applied during the auction system which is studied here. This seems in line with the practices adopted by other exchanges; for instance Comerton-Forde and Rydge (2006 a) described different auction algorithms and they reported that the call auction algorithms of nine out of twelve major exchanges follow this basic principle. Orders which included bargain conditions such as "All-Or-None" were not considered in the pre-open. Orders could also be modified and cancelled during the pre-open.

The NSE circular specifies that one advantage of the proposed pre-open system over the previous one was that it considers market orders in establishing the opening prices. This suggests that market orders were not considered in the call auction system which is studied here; although this could not be established with certainty. The main advantage of considering market orders in the pre-open session is that a price may still be calculated in cases when limit orders specify prices that preclude any matching. Market buy (sell) orders are considered as orders which are prepared to trade at the highest (lowest) available price. Thus, market orders obtain the best price priority and are listed at the top of the order book.

Now, Comerton-Forde and Rydge (2006 a) describe further criteria in auction algorithms which are considered in those cases where there is more than one possible price which results in the highest traded quantity. Whilst no direct information about subsequent criteria applicable on NSE was found, it might be the case that when more than one opening price was possible, the initial price was determined with reference to the previous prices of the security. In fact the above-mentioned circular specifies that: "The proposed algorithm therefore eliminates the need to refer to the Base Price of the security as the opening price if there are limit price orders available in the market".

With reference to transparency, one may reasonably assume that the brokers' information set during the auction was largely the same as that prevailing during the continuous session – although this could not be ascertained with certainty. As described in Section 2.2.2, brokers have access to the best five prices prevailing for each stock and the respective quantities on offer at each price, in real time. Perhaps the only material difference between the auction information set and the continuous trading one relates to the availability of indicative prices prior to the commencement of trade matching. For instance, traders start by submitting orders prior to the commencement of transactions in the opening auction. Similarly, brokers are likely to have access to unfilled orders during the 20 minute break in between the continuous session and the closing auction. This is an important difference – at least on theoretical grounds – given that one characteristic of auctions which potentially makes them more efficient trading mechanisms, is that traders can assimilate existing order information prior to the execution of trades.

Another point which is worthy of comment relates to the measurement of volatility during the call auction. Given that the auction executes a batch of transactions for any particular stock at one single price, it does not make sense to speak of stock-specific volatility during the call auction. Thus, when researchers require an inference on stock-specific volatility during the auction, they would have to measure the price movement for the particular stock from the auction time to the previous or subsequent observations. Despite this, one may still measure the volatility during the auction in terms of a stock index movement. As shares trade successively in the auction, the index value changes continuously. However, when measuring index volatility during the auction, one should keep in mind that this is based on shares trading in a designated alphabetical order, rather than a continuous matching process across all stocks.

The opening and closing auctions were suspended without prior notice on 9th June 1999, and it subsequently emerged that the suspension was due to software-related problems, although these had not apparently had a direct effect on the pricing process. Indeed, if the auctions were resulting in asset mispricing, one may expect that they would have been suspended at an earlier stage in view of the discrepancies prevailing between the call auction prices as compared to those of the continuous session.

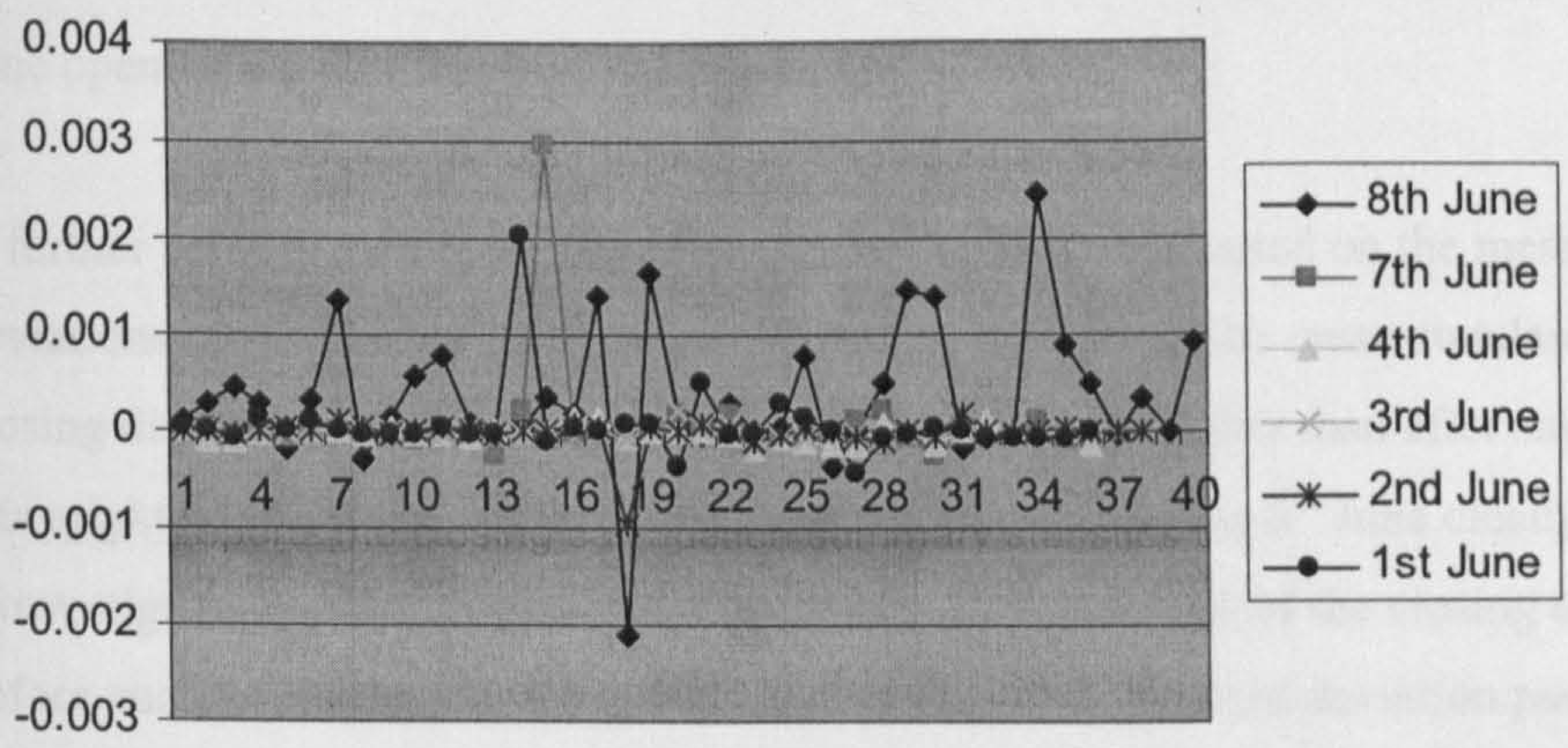
One may deduce that the software glitch mainly occurred in the closing auction held on 8th June 1999 – which would explain the sudden suspension on the subsequent day. Looking at the intra-day data files, the closing call auction held on 8th June may be compared with the closing calls of the preceding five trading days. Statistics reported in Table 6.1 show that the former auction seems ambiguous as compared to the preceding five: its duration is at least double that of the other days, and the interval in between observations is much longer. In addition, the percentage change in the Nifty value is much larger than that registered in the other auctions. During the closing call auction held on the 8th June, the Nifty Index value increased from around 1162 to 1178; yet this movement was reversed during the subsequent day, when the Nifty closed at around 1162 again. This indicates that the increase in Nifty value registered during the 8th June closing auction, may have been unjustified, since it was reversed on the subsequent day. Figure 6.1 shows how the price movements in the latter auction were much higher as compared to those registered on the preceding five trading days.

Table 6.1: Closing Call Auction Summary Statistics

Date	8 Jun 99	7 Jun 99	4 Jun 99	3 Jun 99	2 Jun 99	1 Jun 99
Auction Starting Time	15:50:15	15:50:02	15:50:02	15:50:01	15:50:01	15:50:01
Auction Ending Time	15:59:33	15:52:58	15:53:33	15:53:25	15:53:15	15:54:21
Duration Of Auction (min.' sec.")	9'18"	2'56"	3'31"	3'24"	3'14"	4'20"
% Nifty Change	1.5%	0.3%	-0.1%	0.0%	-0.1%	0.2%
# Observations	41	37	37	38	39	37
Average Interval	14 sec.	5 sec.	6 sec.	5 sec.	5 sec.	7 sec.

The table reports the closing call auction summary statistics for 8th June 1999 as compared to the preceding five trading days. The rows show the following information: Trading Day, Auction Starting Time, Auction Ending Time, Duration of the Auction, the % change in the Nifty Index during the auction, the number of Nifty observations yielded by the auction software programme, and the average interval in between the Nifty observations during the call auction.

Figure 6.1: Closing Call Auctions – Nifty Log Returns



The above plots show the price movements registered during the closing call auctions as given in the intra-day data files provided by NSE. The observations were *not* sampled at uniform time intervals.

This preliminary investigation was extended by looking at the opening and closing Nifty return distributions for the period 26th May 1999 to 22nd June 1999. This includes ten trading days with opening and closing call auctions, and a further ten days without call auctions. If the software problems in the auction system were resulting in unjustified price movements, one should note higher price dispersion during the auctions. Yet, comparing the auction prices to the subsequent prices during the day may be biased against the call auctions – since volatility is typically higher at the opening and at the closing. The opening movements in the call auctions days were thus compared to the opening movements in the continous trading days, and the procedure was repeated for the closing movements. The opening distributions were defined as the first thirty Nifty observations, sampled at 30-second intervals (covering the first 15 minutes of trading). Similarly, the closing distributions were defined as the last thirty Nifty observations, sampled at 30-second intervals. (The latter usually comprise the last 11 minutes of continuous trading, a 20-minute trading break which is treated as a 30-second interval for computation purposes, and the closing call auction).[48]

A series of t-tests were conducted to compare the mean standard deviations for both sets of distributions, as shown in Table 6.2. Two t-tests were conducted on the opening distributions. The mean standard deviation of the opening distributions increased following the suspension – indicating that it was unlikely that any software problems in the auction system were resulting in unjustified price movements. A second test was conducted, to check the difference between the standard deviation of the opening distribution prevailing on 8th June 1999, and the mean standard deviations for the rest of the sample (before and after auction suspension), following the notion that the 8th June opening auction might have driven prices away from fundamentals. The former difference between the standard deviations is insignificant, suggesting that the 8th June opening auction functioned adequately.

A further set of three t-tests, shown in Table 6.2, were conducted on the mean standard deviations of the closing distributions. T-test 3, shows that the mean standard deviation of the closing distibutions before suspension, was significantly higher than after suspension. Yet, this might be solely caused by the high price dispersion of the 8th June closing auction. T-test 4 investigates this by comparing the mean standard deviation of the closing distributions before auction suspension except 8th June, to the mean standard deviation post-suspension. The difference is no longer significant. The fifth t-test compared the 8th June closing distribution standard deviation to that of the rest of the sample (before and after suspension). The test shows that the standard deviation of the 8th June closing distribution was significantly higher than that prevailing over the remaining trading days.

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[48] In this sample period, the returns realized during the trading break did not materially differ from the 30 second returns.

Table 6.2: T-Tests on Opening and Closing Distributions (data sampled at half-minute intervals)			
Opening Returns			
Test 1:	MSD - Before Suspension [MSD - After Suspension]	0.0010	[0.0015]
	t-Statistic [95% one-tailed critical value]	-1.4894	[1.7341]
Test 2:	MSD - 8th June [MSD - Rest of Sample]	0.0015	[0.0013]
	t-Statistic [95% one-tailed critical value]	-0.2759	[1.7341]
Closing Returns			
Test 3:	MSD - Before Suspension [MSD - After Suspension]	0.0005	[0.0004]
	t-Statistic [95% one-tailed critical value]	1.7506	[1.7341]
Test 4:	MSD - Before Suspension except 8th June [MSD - After Suspension]	0.0005	[0.0004]
	t-Statistic [95% one-tailed critical value]	1.4241	[1.7396]
Test 5:	MSD - 8th June [MSD - Rest of Sample]	0.0009	[0.0004]
	t-Statistic [95% one-tailed critical value]	-1.7605	[1.7341]

The above t-tests compared the Standard Deviations for the log return distributions of the Nifty index, sampled at 30-second intervals. The opening distributions comprised the first 29 log returns for each trading day, and similarly the closing distributions consisted of the last 29 log returns for each trading day. The mean standard deviation (MSD) was worked out by taking the average of the standard deviations for each distribution included in the particular sample. The opening distributions show no significant differences before-suspension and post-suspension – indicating that any software problems did not result in unjustified price movements in the opening call auctions. The closing distributions point at a significant difference between the MSD of 8th June 1999, as compared to the rest of the sampled days. This indicates that the software problems might have resulted in unjustified price movements during the closing call auction of the latter day – and the auction was thus suspended on 9th June 1999.

The above evidence, supports the view that the software problems in the auction system mainly occurred on 8th June 1999 during the closing. The auction software glitches are unlikely to have had a direct effect on the pricing process during the rest of the trading days. This notion is important to establish that we are *not* considering a call auction which is inherently defective due to software problems (save for one particular day). Studying a defective auction would not result in any firm conclusions as to the effectiveness of call auctions in general.

The NSE did not subsequently reintroduce opening and closing auctions on a permanent basis. When auctions were in effect, the pre-opening auction was usually held between 09:30 and 09:45, followed by continuous trading until 15:30, and subsequently by a post-closing auction between 15:30 and 15:45. As from the 9th June 1999, continuous trading took place between 10:00 and 15:30. The data period runs from 2nd March through 4th September 1999, or for 63 days either side of 9th of June.[49] The subsequent investigations were conducted on daily data, unless otherwise specified.

In selecting the individual stocks to be included in the sample, only equity securities were considered.[50] The aim of the sampling process was to select the most liquid stocks, in order to guarantee sufficient observations to enable the conduction of a detailed empirical study. Yet, selecting the most liquid stocks, may also lead to results which could be sample specific. For example, overall it would be reasonable to expect higher spreads to prevail for a randomly selected sample, rather than for the most liquid stocks. In addition, some findings might also be specific to the particular period.

Stocks were chosen in terms of the 170 stocks with highest quantities traded, and the 170 stocks with the highest Indian Rupee value traded. 107 stocks appeared on both of these lists, and this lead to a sample of 233 stocks. Thirty stocks were omitted from the sample due to missing observations. Missing observations might lead to a jump in returns when the observations resume again, and this might impact on the calculation of returns and volatility. Some of the missing observations in the sample may have been due to shares suspended from trading for some days, as the company issued additional shares or changed its equity structure.

Where a change in equity structure was detected (including mergers, new share issues and stock splits) the stock was deleted from the sample on the grounds that this is likely to have affected the pricing process. This led to a further reduction of 21 shares from the sample. The final sample thus consisted of 182 stocks as shown in Appendix 6.1.

The sample is characterised by a considerable degree of cross-sectional variation. For example the (simple) return for GRAMOPHONE was 2856.42% whilst the (simple) return for ARVINDMILL was -58.91%. One may also note that during the thirteen months included in the sample period, the Nifty Index value increased by 50.5%, whilst the Midcap Index realized a gain of 99.5%.

[49] Our sample period is characterized by occasional minor changes in trading hours.
[50] In order to eliminate observations which are not related to common equity, the occurrences for securities in the series N1, N2, N3, N4, N5, N6, N7, N8, N9, NA, NB, NE, NO, NP, (debentures), P1 (preference shares) and W1, W2, W3, W4 (warrants) and AE, BE and B1 were deleted. Only observations in the EQ (equity) series were considered.

For the purpose of the event study, observations of the BSE-500 Index were used. There were five instances when the BSE-500 closing price was unavailable, possibly due to BSE being closed for trading. These days were omitted from the sample when conducting the event study.

For the basic comparison analyses and the event study, the sampling interval was homogenised by the use of daily data on volumes and prices (the last trade price for each stock, unless otherwise specified). Appendix 6.2 shows the data periods used for the VEL comparisons and the event study. In calculating returns, dividend payments were abstracted from.

To obtain an idea of the activity in the auctions before suspension, three trading days were selected at random from different days of the week and reasonably close to the event date. Three sub-samples were taken: Sample A securities had a daily pre-event mean volume less than or equal to 40,000 shares, whilst Sample C securities featured a pre-event daily mean volume greater than 140,000 shares. The remaining shares were labelled as Sample B (medium-liquidity shares). The former volume values were chosen in such a way to obtain three approximately equal sub-samples. Summary statistics of trading activity on the chosen days for Sample A, B and C shares are shown in Table 6.3. Evidently, trading frequencies increase as we move from low to medium and to high liquidity stocks, and the level of activity is generally higher for the closing auction than for the opening auction. A possible explanation for this is that any unexecuted orders at the end of the continuous session were automatically carried forward to the closing call, whereas outstanding orders at the end of the previous trading day were not necessarily carried forward to the call auction of the subsequent day.

With reference to notation, the event date (9th June 1999) is denoted as T=0, and all other days are denoted in terms of the number of trading days which separate the respective day from this date. For instance, T+5 refers to 5 trading days after the event day.

The study now proceeds with the assessment of the impact of the discontinuing of call auctions on VEL factors.

Table 6.3: Summary Statistics for Call Auctions

	Monday 3 May 1999		Thursday 27 May 1999		Friday 4 June 1999	
	Open	Close	Open	Close	Open	Close
Total Number of Transactions (including unsampled stocks)	1,274	2,995	1,446	13,361	3,392	5,642
Sample A						
% of shares in Sample A which traded in the auction	7%	46%	13.6%	88%	18.6%	72.9%
Average # of Transactions per share (incl. zero observations)	0.4	1.6	0.5	7.8	0.6	10.1
Average # of Transactions per share (excl. zero observations)	5.3	3.4	3.5	8.8	3.3	13.8
Average # of Units Traded per share (incl. zero observations)	49	217	34	1,307	141	830
Average # of Units Traded per share (excl. zero observations)	725	473	254	1,482	755	1,140
Sample B						
% of shares in Sample B which traded in the auction	45%	80%	41%	95%	39.7%	81.3%
Average # of Transactions per share (incl. zero observations)	2.0	5.0	1.3	21.3	3.1	6.2
Average # of Transactions per share (excl. zero observations)	4.5	6.3	3.2	22.7	8.0	7.6
Average # of Units Traded per share (incl. zero observations)	447	891	409	5,118	786	1,095
Average # of Units Traded per share (excl. zero observations)	986	1,118	1,005	5,459	2,012	1,348
Sample C						
% of shares in Sample C which traded in the auction	80%	95%	95%	100%	86.4%	98.3%
Average # of Transactions per share (incl. zero observations)	13.6	28.5	14.7	120.1	42.0	59.9
Average # of Transactions per share (excl. zero observations)	17.1	30.0	15.4	120.1	48.5	60.9
Average # of Units Traded per share (incl. zero observations)	4,290	8,201	4,117	43,515	15,243	19,912
Average # of Units Traded per share (excl. zero observations)	5,385	8,640	4,338	43,515	17,634	20,255

The table shows summary statistics for the opening and closing call auctions held on three different days. The days were randomly selected, yet trading days which were more than one and a half months distant from the event were not considered. In addition, if the chosen date happened to be a Monday, all other Mondays were no longer considered, and so on for all the other days. This was done in order to minimize the possibility of bias from day of the week effects. As expected, trading frequencies increase as we move from Sample A to Sample B to Sample C. The statistics indicate that the closing call auction is more active than the opening auction.

6.4 The Impact of Auction Suspension on Volatility

The impact of the suspension of the call auctions on market volatility is assessed through a comparison of the percentage intra-day price difference and reversals of overnight returns. These measures focus on short-term volatility, given that any expected impacts of call auctions to price stability are essentially of a short-term nature.[51]

6.4.1 The Scaled Intra-Day Price Difference

The scaled intra-day price difference (SIDP) is an indicator of intra-day volatility given by:

$$SIDP_{i,t} = (P_{high\ i,t} - P_{low\ i,t}) \ / \ P_{open\ i,t} \tag{6.1}$$

where $P_{high\ i,t}$, $P_{low\ i,t}$ and $P_{open\ i,t}$ are the highest, lowest and opening prices for security i on day t respectively. This measure may be taken as an indication of the efficacy of opening call auctions on the grounds that if auctions aggregate information more efficiently, they should lead to lower intra-day volatility around the fundamental value of the security. The pre-event $SIDP_{i,t}$ was worked out using data from T-63 to T-1, whilst in estimating post event $SIDP_{i,t}$ the data from T+1 to T+63 was used.

Results are shown in Table 6.4. Contrary to expectations, intra-day volatility decreased in the post-event period, and the hypothesis of no difference between the pre-event and post event $SIDP_{i,t}$ is clearly rejected through a paired two sample t-test for means. Paired Means t-tests were also conducted on the standard deviations of $SIDP_{i,t}$ for each stock, and this may be interpreted as the "volatility of intra-day volatility". No significant change in the standard deviation of $SIDP_{i,t}$ is evident and the null hypothesis of no difference between pre-event and post-event data is not rejected.

[51] The impact of the suspension on longer-term volatility is investigated in Chapter 7.

Table 6.4: Tests on Scaled Intra-Day Price Difference (Daily Frequency)		
	Pre-Event	Post-Event
Mean $SIDP_{i,t}$	0.0632	0.0564
Std. Deviation of $SIDP_{i,t}$	0.0211	0.0226
t Statistic on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	7.6443	
99% Critical Value (one-tailed test)	*2.3471*	
99% Critical Value (two-tailed test)	*2.6033*	
Mean of Standard Deviations of $SIDP_{i,t}$	0.033166	0.033157
Std. Deviation of Std. Devn's of $SIDP_{i,t}$	0.0165	0.0491
t Stat on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	0.0027	
90% Critical Value (one-tailed test)	*1.2862*	
90% Critical Value (two-tailed test)	*1.6533*	

The table shows the results of paired two sample t-tests for differences in intra-day volatility between the pre-event and post-event period. Tests on the Means of the Scaled Intra-Day Price Difference ($SIDP_{i,t}$), reject the null hypothesis of no change in $SIDP_{i,t}$, following suspension at the 99% level of confidence. When considering the standard deviations of $SIDP_{i,t}$, the null hypothesis cannot be rejected, denoting no significant change in the standard deviation of $SIDP_{i,t}$ following suspension.

6.4.2 Overnight Return Reversal

Overnight return reversals (ORR) are a measure of inter-day volatility. If the auctions help in price discovery, one may expect lower overnight volatility during the period when auctions were held. However, a direct comparison between overnight returns in the pre-event and post-event periods could be potentially misleading as higher price changes in one period might be justified by the news in that period. Thus it might be more appropriate to concentrate on the reversal of price movements. If overnight price movements are reversed during the next day, this implies that the overnight movement was excessive. Thus, the day return is regressed as a function of the previous overnight return as follows:

$$r_{i,t} = \mu_i + \pi_i r^o{}_{i,t} + \varepsilon_{i,t} \qquad (6.2)$$

where μ_i is a constant, $r_{i,t}$ is the day (log) return of security i on day t, $r^O_{i,t}$ is the overnight (log) return of security i between day t-1 and t, and $\varepsilon_{i,t}$ is an error term. A negative π_i may be taken as an indication of price reversals, and therefore excess overnight volatility.

The mean overnight return reversal coefficient π_i was estimated for both the pre-event and post-event period of the sampled stocks, as shown in Table 6.5. The mean coefficient of π is negative both in the pre-event and in the post-event period, which is an indication of excess short term volatility in terms of overnight return reversals. The ORR test indicates a highly significant increase in the modulus of π when the call auctions were suspended, as inferred through a paired two sample t-test for means.

Table 6.5: Overnight Return Reversals (Daily Frequency Data)

	Pre-Event	Post-Event
Mean π	-0.3439	-0.3970
Standard Deviation of π	0.1726	0.2288
t Statistic on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	2.9097	
99% Critical Value (one-tailed test)	*2.3471*	
99% Critical Value (two-tailed test)	*2.6033*	

The table shows the results of a paired two sample t-test for differences in overnight return reversal coefficients (π) between the pre-event and post-event period. The test shows that reversals became higher in magnitude following suspension. The difference is significant at the 99% confidence level and this suggests lower overnight volatility during the auction period.

Thus, the above tests yield contrasting results as to changes in volatility following the auction suspension. In order to cross-check that there were no additional events which might have impacted on volatility during this period, NSE circulars for the period in question were reviewed. On 16th June 1999 the National Securities Clearing Corporation (NSCC) applied additional volatility margins in respect of outstanding positions of trading members (brokers) in highly volatile stocks. This might have discouraged members from increasing positions in volatile stocks and might have resulted in lower volatility in the post-suspension period. It might also be the case that brokers charged higher fees for transactions in these stocks, and this might have discouraged trading activity in these stocks. Yet, the first instance where any NSE circular specified particular stocks on which this margin was applied was on the 4th January 2000, which is outside the data range used in this exercise. In addition, when analysing the specific stocks on which an additional volatility margin was applied, it was noted that only four of these stocks featured in the sample. Overall, this indicates that additional volatility margins were not likely to have been the underlying cause of the changes in volatility.

A more general issue is that most Indian companies have accounting years which end in March, and release their annual reports between March and June, in the pre-event window, as described in Chapter 5. It could therefore be argued that one might expect higher volatility in the pre-event window because of the clustering of earnings reports. However, Ball and Brown (1968) found that the impact of an earnings surprise on a company's share price typically begins several months before the release of the annual report, and is almost fully impounded into the price by the time of the formal earnings announcement. Furthermore, the impact of the news on share prices and spreads is generally dissipated during the day of the announcement itself in as little as 15 to 30 minutes as outlined by Patell and Wolfson (1984) and Kim and Verrecchia (1994). This suggests that any effect of such announcements on pre-event window volatility would have been at most small, and in any case confined to the SIDP measure.[52]

Notwithstanding the above arguments, a data adjustment procedure was carried out to account for the volatility patterns during different months of the year on NSE. The latter procedure confirmed that the effect of volatility seasonality on the former results is minimal. The volatility seasonality regressions presented in Chapter 5 Table 5.8 were used to adjust the individual stock figures on which the former volatility tests were based. The volatility seasonality model shows that the SIDP is typically 0.008 higher during the months of March and April. This implies that around two-thirds of the pre-event observations of the SIDP for each individual stock have to be scaled down by 0.008. As a substitute for this procedure, the final SIDP for each individual stock during the pre-event period was adjusted down by two-thirds of 0.008. Similarly, given that the volatility seasonality model shows that the SIDP is typically 0.0039 lower during August, around one-third of the post-event observations for each individual stock have to be adjusted upwards by 0.0039. Again, this procedure was approximated by an upward adjustment of the final SIDP of individual stocks by one-third of 0.0039. Tests on Paired-Two Samples for Means for the adjusted SIDPs shown in Table 6.6 Panel A, still indicate a drop in SIDP following suspension which is significant at the 99% level of confidence.

[52] NSE regulations permit release of earnings news at any time in the trading day, and so there is no overnight effect arising from the systematic release of earnings news out of trading hours.

Similar adjustments were done in respect of the ORR measure. The ORR was adjusted for the seasonality pattern which is typical in the Modulus of Log Returns for Daily Data, shown in Chapter 5 Table 5.8. Given that the Return Modulus is typically 0.0043 higher during the months of March and April, around two-thirds of the ORR pre-event observations for each individual stock have to be roughly scaled down by 0.0043. In this way, the final ORR modulus for each individual stock during the pre-event period was adjusted down by two-thirds of 0.0043. Similarly, given that the Return Modulus is typically 0.0026 lower during August, around one-third of the post-event observations for the individual stocks have to be adjusted upwards by 0.0026. Again, this procedure was approximated by an upward adjustment of the final ORR modulus of individual stocks by one-third of 0.0026. Tests on Paired-Two Samples for Means for the adjusted data shown in Table 6.6 Panel B, confirm that ORRs became more prevalent following suspension, where the change is still significant at the 99% level of confidence.

Table 6.6

Panel A: Scaled Intra-Day Price Difference (Seasonally Adjusted Daily Data)

	Pre-Event	Post-Event
Mean $SIDP_{i,t}$	0.0628	0.0565
Std. Deviation of $SIDP_{i,t}$	0.0210	0.0227
t Statistic on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	7.1823	
99% Critical Value (one-tailed test)	*2.3471*	
99% Critical Value (two-tailed test)	*2.6033*	

Panel B: Overnight Return Reversals (Seasonally Adjusted Daily Data)

	Pre-Event	Post-Event
Mean π	-0.3429	-0.3973
Standard Deviation of π	0.1721	0.2290
t Statistic on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	2.9836	
99% Critical Value (one-tailed test)	*2.3471*	
99% Critical Value (two-tailed test)	*2.6033*	

The above paired two sample t-tests, replicate the tests shown in Tables 6.3 and 6.4, using seasonally-adjusted data. These tests do not change the former inferences, in that the they indicate a drop in SIDP following suspension (significant at the 99% confidence level) and an increase in magnitude of the ORRs following suspension (significant at the 99% level of confidence).

These adjustments confirm the arguments that the typical volatility seasonality pattern on NSE does not impact on the former volatility tests. Yet, this still does not solve the puzzle regarding the conflicting highly significant inferences which were obtained. Overall, the volatility tests do not clarify whether the auctions were reducing market volatility. The contradictory findings on intra-day and overnight volatility might be potentially explained by the statistics shown in Table 6.3 that the closing call auction was more active than the opening one. Following the suspension of the auctions, intra-day volatility decreased – possibly due to the fact that the opening auction was not sufficiently effective given the relatively low activity. The pronounced overnight volatility following suspension might indicate that the closing call auction was more effective due to higher activity. This is corroborated by the findings of Hillion and Suominen (2004), who found that closing call auctions may reduce the potential for market participants to manipulate closing prices.

It should also be noted that the former tests are not exhaustive. For instance, the tests do not address the issue of whether the call auctions' utility is higher on more volatile days, in terms of their contribution to enable the market to deal with news shocks. The relationship between volatility and news is addressed through GARCH models in Chapter 7, where a more detailed investigation of the impacts of the auction suspension on NSE volatility is undertaken.

This investigation now proceeds with further tests on Efficiency and Liquidity, which are carried out using the original data (*not* adjusted for monthly seasonality).

6.5 The Impact of Auction Suspension on Pricing Efficiency

6.5.1 Relative Return Dispersion

The Relative Return Dispersion (RRD) as described by Amihud, Mendelson and Lauterbach (1997), is calculated by averaging the squared residuals of the market model. RRD is defined as:

$$RRD_t = \frac{1}{n}\sum_{i=1}^{n}\varepsilon^2_{it} \qquad (6.3)$$

where RRD_t is the Relative Return Dispersion across the sampled securities during time t, ε_{it} is the market model residual for security i at time t, and n is the number of sampled securities. A lower RRD_t indicates a lower pricing error and therefore higher efficiency. Results shown in Table 6.7 indicate that RRD decreased contrary to expectations, indicating higher pricing efficiency following the auction suspension. The decrease in RRD is significant at the 99% level of confidence, as inferred through a paired two sample t-test for means.

Table 6.7: Relative Return Dispersion (Estimated through Daily Frequency Data)

	Pre-Event	Post-Event
RRD_t	0.1272	0.1017
Standard Deviation of $RRD_{i,t}$	0.1196	0.1127
t Statistic on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	2.9308	
99% Critical Value (one-tailed test)	*2.3471*	
99% Critical Value (two-tailed test)	*2.6033*	

The table shows the results of a paired two sample t-test for differences in relative return dispersion (RRD_t) between the pre-event and post-event period. The test shows a decrease in (RRD_t) following suspension, which is significant at the 99% confidence. This suggests increased efficiency following suspension.

6.5.2 Serial Correlations of Returns

Significant serial correlation in (log) returns may be taken as an indication of pricing inefficiency since if prices fully adjust to new information, price changes should be uncorrelated, assuming that news are uncorrelated as well. The pre-event and post event first order autocorrelations for individual stocks are reported in Appendix 6.3, together with Box-Pierce (1970) and Ljung-Box (1978) statistics. As may be expected, some stocks showed negative first order serial correlation, whilst others showed positive serial correlation. Given this, the mean correlation across stocks is expected to converge to zero. Thus it makes sense to look at the squared first order correlations.

One should note that the first order serial correlation for most stocks was insignificant, both in the pre-event and in the post-event estimation (Appendix 6.3). Table 6.8 shows that the first order serial correlation changes significantly, yet this result can be misleading since the significance stems from the fact that a predominantly negative serial correlation changed to a predominantly positive serial correlation. Whilst this may suggest that the nature of the price discovery process may have changed following the call auction suspension, one should note that positive serial correlation is as "inefficient" as negative serial correlation, and therefore this result should not be interpreted as a change in efficiency. Looking at the change in the squared correlation coefficients, we note an insignificant increase in pricing efficiency. This exercise thus confirms the improvement in market efficiency following suspension as inferred through the previous test, albeit insignificantly.

Table 6.8: Return Serial Correlations for Daily Frequency Data				
	First Order Serial Correlation		*Squared First Order Serial Correlation*	
	Pre-Event	Post-Event	Pre-Event	Post-Event
Mean	-0.0169	0.0791	0.0304	0.0292
Standard Deviation	0.1739	0.1519	0.0409	0.0352
t Statistic on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	-6.3912		0.2748	
95% Critical Value (one-tailed test)	*1.6533*		*1.6533*	
95% Critical Value (two-tailed test)	*1.9732*		*1.9732*	

The table shows the results of paired two sample t-tests for differences in serial correlation between the pre-event and post-event period. The first test indicates a highly significant change in serial correlation where the latter changed from negative dependence to positive dependence. Yet, given that both negative and positive serial correlation constitute a sign of inefficiency, one should look at the absolute value of the correlation or alternatively at the squared correlation. This is done in the second test, which indicates an insignificant decrease in squared correlation coefficients following suspension.

Given that auctions are thought to have particular value at the opening of the trading day, when it is necessary to aggregate overnight information, the investigation was extended to how the call auctions performed in terms of their role in helping with price discovery on NSE. If the call auctions were beneficial for price discovery purposes, then one may expect that prices move quickly to their fundamental values and this should lead to lower serial correlation of returns in the call auction regime – particularly at the beginning of the day following the opening auction.

This issue was tackled through intra-day data for the NSE Nifty Index by taking the logarithmic returns of the index sampled at one minute intervals.[53] The sample started with the last 26 trading days of the call auction regime (4th May 1999 – 8th June 1999) and the first 26 trading days of the post-auction regime (9th June 1999 – 14th July 1999). Two trading days were dropped from this sample due to trading suspensions occurring during the first hour of the day which occurred on the 21st May 1999 and on the 28th June 1999 respectively. Thus, the sample used for the purpose of this exercise included 25 trading days in each regime.

[53] The data for the Nifty Index was used (rather than individual stock data) to avoid the problem of non-trading in individual stocks.

The first order serial correlation coefficient of the first 60 log returns of the Nifty index sampled at one minute intervals was estimated for each trading day. As shown in Table 6.9, in case of the auction regime the cross-sectional average of the serial correlation coefficients of the sampled trading days was 0.369, whilst in case of the post-auction regime this statistic was 0.226. A t-test on the serial correlation coefficients of both regimes enabled the rejection of the hypothesis of equal means at the 99% confidence level.[54]

Table 6.9: Nifty Index Serial Correlation During the First Trading Hour (Nifty observations were sampled at one-minute frequency)

	Pre-Event	*Post-Event*
Mean	0.3690	0.2261
Variance	0.0123	0.0365
Pooled Variance	0.0244	
T Statistic on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	3.2352	
99% Critical Value (one-tailed test)	2.4066	
99% Critical Value (two-tailed test)	2.6822	

The table shows the Nifty Index First Order Serial Correlation Coefficients in the Auction and Post-Suspension period. The mean correlation is an average of the first order serial correlation coefficients estimated through a sample of 25 trading days for each regime.

This suggests that the call auctions did not help in price discovery, even at the opening. Thus, pricing efficiency generally increased after auction suspension, both during the whole trading day and in particular within the first hour.

6.6 The Impact of Auction Suspension on Liquidity

The measures which were selected for investigating liquidity changes following suspension were the number of shares transacted and the volume per unit of return. The results were then cross-checked through a time trend regression.

6.6.1 Number of Shares Transacted

The number of shares transacted is related to the "volume" aspect of liquidity, in the sense that higher amounts of activity are expected in a more liquid market. The results presented in

[54] The same qualitative results are obtained when considering the modulus of the serial correlation coefficients, given that positive serial correlation is as inefficient as negative serial correlation.

Table 6.10 Panel A, show increased volumes following auction suspension. This increase is significant at the 90% confidence level, as inferred by a paired two sample t-test for means.

Table 6.10: Liquidity Indicators		
Panel A: Daily Volume of Transactions		
	Pre-Event	Post-Event
Mean of Volume	322,391	367,123
Std. Deviation of Volume	986,908	942,824
t Stat on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	-1.9422	
90% Critical Value (one-tailed test)	1.2862	
95% Critical Value (one-tailed test)	1.6533	
90% Critical Value (two-tailed test)	1.6533	
95% Critical Value (two-tailed test)	1.9732	
Panel B: Daily Volume / Return Ratio		
	Pre-Event	Post-Event
Mean of (Volume / Return) Ratio	108,730	141,148
Std. Deviation of (Volume / Return) Ratio	284,978	338,722
t Stat on the Null Hypothesis of No Difference between Pre-and Post Event (Paired Means Test)	-4.4228	
99% Critical Value (one-tailed test)	2.3471	
99% Critical Value (two-tailed test)	2.6033	
The table shows the results of paired two sample t-tests for differences in liquidity proxies between the pre-event and post-event period. The first test (Panel A) shows an increase in the number of shares transacted following suspension which is significant at the 90% level of confidence. The second test (Panel B) shows an increase in the volume: return ratio following suspension which is significant at the 99% confidence. The tests suggest increased liquidity following the auction suspension.		

6.6.2 Volume per Unit of Return

The volume divided by the absolute return, is an estimate of what amount of traded shares causes a one unit change in stock price.[55] Therefore, this measure assesses the "resiliency" aspect of liquidity. The absolute return is defined as the modulus of the difference between the opening and the closing price of the security. As may be expected, the return on some days was zero and this was problematic given that in such cases a ratio of infinity is obtained. Thus, for computation purposes, the daily Return / Volume ratio for the stocks was estimated

[55] The volume measure being used is the number of shares transacted, rather than the monetary value of the transacted shares.

and the reciprocal of the average of the daily ratios for each stock was taken as the average Volume / Return ratio. This method only leads to "infinity occurrences" when the volume is equal to zero i.e. when the share does not trade for the whole day. No such instances occurred in the sample at hand.

Results presented in Table 6.10 Panel B, show a statistically significant increase in market liquidity in terms of resiliency, given that a higher volume is required to change the price by one unit.

6.6.3 A Time-Trend Model

Both of the above tests suggest increased liquidity, yet one cannot exclude the possibility that the latter improvement in resilience, may have been partly due to a lower degree of intra-day volatility, as shown in Section 6.4.1. The liquidity tests should be interpreted with caution, given that the number of shares traded on most world exchanges is on the increase – and thus the above increase in liquidity might be unrelated to the call auction suspension. This implies that one may expect share volumes to trend upwards, irrespective of the call auction suspension. This point was addressed by looking at a longer data period from 1st January 1995 to 29th December 2003 – a total of 2,248 daily observations. The test consisted of an estimation of a simple time trend regression for volume traded with shift and trend dummies at the suspension date:

$$v = c + \beta_1 t + \beta_2 d + \beta_3 t.d + \varepsilon \qquad (6.4)$$

where v is the logarithmic volume data relating to the total number of transactions on NSE, t is a time trend starting from 1 on the first observation and increasing successively to 2,248 at the last observation, d is a dummy variable taking a value of zero from the initial observation till auction suspension date, and a value of one in the successive period, c, β_1, β_2, and β_3 are estimated coefficients, whilst ε is an error term. Results shown in Table 6.11 provide confirming evidence that that there was a significant step increase in volume as shown by the t and d coefficients, though a small decrease in trend following the auction suspension as shown by the $t.d$ coefficient.

Overall, these tests confirm an increase in NSE liquidity following auction suspension, which goes beyond a simple longer-term trend towards higher volumes as witnessed on most world exchanges. One may thus rule out any hypothesised deterioration in liquidity levels, following the suspension of the call auctions.

Table 6.11: Time trend regression estimated through daily data

	constant	trend	d	d x trend
Coefficient	9.4426 ***	0.0033 ***	2.0490 ***	–0.0021 ***
T-ratio	(348.8)	(78.5)	(27.9)	(36.6)

The table shows the results obtained for a time trend regression for volume traded on NSE between January 1995 to December 2003 (2248 observations). The explanatory variables are an intercept, a time trend, a dummy variable taking the value of zero before the auction suspension and a value of one following the suspension, and the final variable is the dummy multiplied by the time trend. The first row shows the coefficients, whilst t-ratios are shown in brackets underneath. Statistical significance at the 99% level of confidence is denoted by ***.

In summary, the evidence on VEL changes is not unambiguous, but a substantial majority of the tests suggest that there was an improvement in VEL following the auction suspension.

6.7 The Value of Auctions to Shareholders: An Event Study

This section uses event study methodology to assess the value of auction suspension to shareholders. A description of event-study methodology is offered in Section 6.7.1, whilst Section 6.7.2 discusses the limitations of the methodology. The empirical results are presented in Section 6.7.3.

6.7.1 Event Study Methodology

Event study methodology analyses "normal" stock returns in order to compare them to the returns realized over a period of interest, during which a specific event took place. Therefore, this methodology uses the assessment of market participants, in order to infer whether specific events change the value of securities. An event may be deemed to affect the value of securities if the latter experience significant abnormal returns during the event period. According to the theory of market efficiency (Fama *et al.* 1969), prices adjust quickly to new information and therefore one may expect abnormal returns to occur on the event announcement date. Abnormal returns realized immediately prior to the announcement might signify insider trading, whilst abnormal returns on the days following the announcement might be explained by investors reacting to price movements of previous days, prices failing to fully adjust because of daily price limits, and in some cases time zone differences. One important factor which the researcher should consider is whether the observed abnormal returns might emanate from an unrelated event. In this way, the events included in the sample should ideally span over different securities, and have occurred in different periods. The latter might not always be possible, such as when assessing the impacts of a one-time event, say, new legislation or market-wide changes in the trading process.

The period during which the abnormal returns are expected is called the event window, and this usually includes days preceding and following the event date or the event announcement date. It is customary for the event window to commence around two days prior to the event. When the event day is known with certainty, and there are sufficient grounds to believe that markets adjust instantly, a short event window might be appropriate. This study uses an 18 day event window; from T-2 to T+15. The choice of a fairly long window covers the possibility that market microstructure changes of this kind might take longer for the markets to evaluate, partly because they might be interpreted differently by different market participants. Indeed, a high number of participants may also classify such changes as irrelevant, since they are not expected to change the "fundamental value" of securities – in terms of the underlying earnings and risks of the firms. Longer event windows might not necessarily be desirable, on the grounds that the observed returns pattern may become "diluted" with unrelated factors. In addition longer event windows reduce the power of the tests (MacKinlay; 1997) and exacerbate the problem that the assumed normal return generating process is usually imprecise (Fama; 1998).

The market model is estimated through data observed during the estimation window in order to infer the level of normal market returns. The conventional methodology is for the estimation window to precede the event window. Yet, this may lead to post-selection bias, if the particular event is conditional on the characteristics of the securities. For instance, Amihud, Mendelson and Lauterbach (1997), studying an event for stocks selected by the Tel Aviv Stock Exchange on the basis of their "marketability", used a post-event estimation window. In the current study, a pre-event estimation window is used, on the grounds that the event under review was not conditional on stock characteristics, but applied to all NSE securities. According to MacKinlay (1997), event studies may include both pre-event and post-event data for the estimation of normal returns.

Event studies customarily use the market model, estimated through OLS. The market model hypothesises a linear relationship between the return on individual securities and the general market return. Thus:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \tag{6.5}$$

where $r_{i,t}$ is the (log) return of stock i on day t, $r_{m,t}$ is the market (log) return, α_i and β_i are estimated coefficients, and $\varepsilon_{i,t}$ is a residual term. This approach is advantageous not only due to the inherent simplicity, but also due to technical reasons. For instance Brown and Warner (1980), MacKinlay (1997), Fama (1998) and Saiful Bahri and Leger (2001) argued that more elaborate models, such as multifactor ones where additional indices / risk factors are included, do not usually present significant gains. Similarly, Cable and Holland (1999) empirically showed that the market model tends to outperform the other principal return-generating models.

Following, Green, Manos, Murinde, and Suppakitjarak (2003), the above market model was adjusted to account for calendar time effects, on the hypothesis that returns might follow a calendar day pattern rather than a trading day pattern. Thus, the estimated regression was:

$$r'_{i,t} = \alpha_{i,t} + \beta_i r'_{m,t} + \varepsilon_{i,t} \tag{6.6}$$

where $r'_{i,t} = r_{i,t} / m_t$, $r'_{m,t} = r_{m,t} / m_t$ and m is the return interval in calendar days. All of the sampled stocks traded every day during the period of interest, and thus no adjustments were necessary to allow for thin trading.

Following the estimation of the calendar day market model, abnormal returns during the event window are calculated as follows:

$$AR'_{i,t} = r'_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i r'_{m,t}) \tag{6.7}$$

where $AR'_{i,t}$ is the (calendar day) abnormal return for security i on day t. The "trading day" abnormal return is obtained by multiplying $AR'_{i,t}$ by the number of calendar days between the trading days as follows:

$$AR_{i,t} = AR'_{i,t}\, m_t \tag{6.8}$$

The above abnormal returns for each day are then averaged across the stocks as follows:

$$MAR_t = \frac{1}{n}\sum_{i=1}^{n} AR_t \tag{6.9}$$

where MAR_t denotes mean abnormal returns during time t, and n is the number of stocks in the sample. This procedure should help in eliminating the "noise" emanating from firm specific events, which are unrelated to the event under review. Finally, the average abnormal returns are summed across trading days as follows:

$$CAR_t = \sum_{t=T-2}^{T+15} MAR_t \tag{6.10}$$

where CAR_t denotes cumulative abnormal returns during time period t. This enables the detection of abnormal returns in those cases when the event date is not known with certainty, or in those cases where there are reasons to believe that the markets reacted to the information on some other day close to the event, say, due to insider trading. Yet, this methodology has its drawbacks. Brown and Warner (1980) showed that CARs may deviate substantially from zero, even in the absence of any abnormal returns – a feature that may be expected when simulating a random walk.

The use of daily data in event studies warrants a note. Brown and Warner (1985) showed through simulations that using daily (as opposed to monthly) data enhances the predictions of event studies, largely because this permits the specification of a more specific event window. Yet, the authors also discussed problems which are usually encountered when using daily data for conducting event studies. These issues may be summarised as follows:

- Daily stock returns (including excess returns) are not normally distributed, yet they converge to the normal distribution as the sample size is enlarged, in line with the Central Limit Theorem.

- Data sets are usually subject to different trading intervals, due to non-synchronous trading. This feature may result in biased and inconsistent β estimates, when using OLS technique. In particular, the estimated β of highly liquid shares will be biased upwards, whilst that of less liquid securities would be understated, as discussed in Dimson (1979). Yet, Brown and Warner (1985) argued that this does not necessarily imply a flawed overall procedure, given that since OLS residuals sum to zero, the bias in β is compensated for by a bias in α for each security. In addition, when the sample includes securities of differing liquidity levels, and when event dates are not clustered, the bias of the estimated *betas* may be neutralised across securities. Alternative procedures for estimating β were specified by Scholes and Williams (1977) and Dimson (1979), yet Brown and Warner (1985) showed through simulations that these methodologies perform similarly to OLS in terms of specification and power of tests for abnormal performance.

- Estimating the variance of excess returns is often required for the purpose of testing for statistical significance. This task is hurdled by a number of issues, which include serial dependence of excess returns, cross-sectional dependence of excess returns (especially when the event for different securities is clustered within a short period), and non-stationarity in stock return variance, given that the latter tends to increase around specific events. When adjusting for serial correlation, superior test statistics may be computed, yet the "improvements are small, and only apply in special cases"[56]. In the absence of adjustment for cross-sectional dependence (when this is present) the variance is understated and this implies that it would be easier to reject the null hypothesis of no excess returns. Yet, adjusting for cross-sectional correlation may make it more difficult to reject the null hypothesis of no excess returns. Brown and Warner (1985) suggested that such adjustments should only be undertaken when the cross-sectional dependence is high, for example when the securities are selected from one specific industry. When the return variance increases during the event period, the estimated variance (from non-event period data) understates the true variance, and the null hypothesis of no abnormal returns is rejected more frequently. One possible

[56] Brown and Warner (1985).

approach to deal with this problem is to estimate the cross-sectional variance of excess returns using event-period data. Yet, if this approach is undertaken when there are no actual variance changes around the event period, this may lead to sub-optimal variance estimates given that the non-event period variance is ignored.

- The distribution of the test statistic through which the researcher can infer the significance of excess returns is affected by a variety of factors, including those which affect the mean and variance of the excess returns discussed above.

Another decision faced by researchers when conducting an event study concerns the choice of the market index. According to MacKinlay (1997) event studies usually use a broad-based index as a proxy for the market portfolio such as the S&P 500. Brown and Warner (1980) also considered the use of a Value-Weighted Index. While there are no evident gains from this methodology, the authors specified that when using a Value-Weighted Index, the statistics for individual securities should be similarly weighted for the purpose of aggregation – otherwise it might turn out to be "too easy" or "too difficult" to reject the null hypothesis, depending on the estimated *betas* of the stocks in the portfolio.

The choice of index for this study is the BSE 500, a broad based index quoted by BSE. The main reason for this choice of index is that the main indices quoted on NSE at the time – Nifty and Midcap comprise 50 stocks each and therefore they might not be sufficiently broad. In addition, given that major stocks are quoted both on NSE and BSE, and given that both exchanges are subject to the same systemic risk (related to the Indian economy) there are sufficient grounds to believe that this choice of index is reasonable.

In some cases, the researcher may form expectations about whether the event being analysed is likely to positively or negatively affect the value of securities. For instance, one usually expects positive abnormal returns for companies on which a take-over bid is announced. Similarly, one may expect negative abnormal returns for companies which experience a downgrade in their credit rating. Yet, in case of some particular events, expectations cannot be easily formulated. This is the case with stock market microstructure modifications such as changes in trading protocols. In such cases, even if theory posits a relationship between the event and returns, market participants might still take long to trade on the new information, given that such relationship may not be as clear cut to the former. This might be the case with the event studied here.

Tests for inferring abnormal returns include parametric and non-parametric ones. Brown and Warner (1980) found that parametric t-tests are acceptably specified. When using such parametric tests to assess abnormal performance, the researcher is assuming that the test statistic is student-t distributed and security returns are normally distributed. Given that violations of these assumptions may lead to false inferences, non-parametric tests are at times used. These include sign tests and Wilcoxon sign rank tests. The sign test is based on the notion that positive returns should constitute around half of total returns, in a sample where there are no abnormal returns. The Wilcoxon sign rank test considers the magnitude of returns, in addition to the sign. Brown and Warner (1980) noted that such tests may suffer from misspecification, and therefore offer no clear-cut advantages over parametric ones. Researchers should not place unwarranted reliance when using both types of tests.

The power of the test is the ability to reject the null hypothesis of no abnormal returns, for a given level of Type 1 or Type 2 error and a given level of abnormal performance. Large sample sizes, short event windows and abnormal returns of high magnitude, enhance the power of the tests (MacKinlay; 1997).

6.7.2 Other Limitations of Event Study Methodology

Various authors have investigated whether the inherent assumptions of event study methodology constitute a hindrance to the validity of the empirical results. For instance, when testing for the presence of abnormal returns, the researcher has to assume a particular sampling distribution under the null hypothesis (usually a Student-t distribution). Type 1 and Type 2 errors may be made, especially if the assumed distribution differs from the actual one. In particular, the methodology assumes that asset returns are normally and independently and identically distributed across time. This may not always be the case since return distributions tend to deviate from normality. Methods of dealing with such factors include robust estimation as suggested by Mills, Coutts, and Roberts (1996). Yet according to Cable and Holland (2000) this does not necessarily lead to significant benefits, partly because when the abnormal returns are averaged across a large number of stocks, the deviations from normality will tend to become less pronounced. According to MacKinlay (1997), the distribution-related assumptions do not usually present any major problems.

Brown and Warner (1980) noted that the return generating model is subject to measurement error. This limitation is relevant even when a simple market model is chosen, given that according to Roll (1977) the market portfolio cannot be directly observed. This problem becomes more complex when coupled with small sample size.

Event studies are based on the notion that stock prices respond immediately to news. Now, various studies as cited by Fama (1998) suggest that stock returns may at times overreact or underreact following an event, and a correction is observed over the longer term. Such overreactions may be attributed to psychological factors such as traders overemphasising recent information, and informed investors who overestimate the precision of their private information. Yet, Fama (1998) argues that whilst the latter factors may explain individual anomalies or exceptions, they are largely incapable of explaining the "big picture" i.e. the way in which markets usually react to information. Furthermore, the author argues that these "anomalies" tend to disappear when abnormal returns are measured through alternative return generating models.

The empirical results obtained in event studies may be vulnerable to excessive influence by outliers; again a larger sample should reduce such eventualities.

Standard OLS regression, assumes that error terms are homoskedastic, normally distributed and that they are not serially correlated. In the absence of this, the estimated coefficients do not have BLUE (Best Linear Unbiased Estimator) properties. Thus, when estimating the market model, one should check whether the error terms violate these assumptions. Coutts, Mills and Roberts (1994) documented that such violations occurred persistently when working with different data sets, and they attributed this to an inherent misspecification in the market model.

The results obtained in event studies may be particular to the sampled stocks, and in such cases they fail to reflect the behaviour of the whole population. This is particularly relevant in those cases where the sample is not randomly selected. Yet, when selecting a random sample, differing results can still be obtained across different samples as shown by Coutts, Mills and Roberts (1997). In the latter study, whilst different samples usually yielded similar results such as negative CARs after a given time from the event, some samples yielded CARs in a different direction.

When using the estimated market model coefficients to calculate the expected returns during the event window, the researcher is assuming that these parameters are stable over the estimation period and the event window. Coutts, Mills and Roberts (1994) quoted various research papers which demonstrated that the model parameters tend to be unstable.[57] Similarly, Saiful Bahri and Leger (2001) suggested that stock sensitivity to specific risk sources may vary over time. Unstable parameters may imply a flawed estimation of abnormal returns. If the parameters vary during the period being analysed, then the error terms would be heteroskedastic, and therefore testing for heteroskedasticity in the error terms may be one way of inquiring whether the parameters were stable over the period.

Coutts, Mills and Roberts (1997) noted that when parameters are unstable, the estimation of abnormal returns is partly dependent on the number of days included in the estimation period (given that different estimation periods yield different parameters). Despite this, the overall pattern of cumulative abnormal returns is largely unaffected by these factors, since the main effect is simply to drift the pattern downwards or upwards. Given these limitations, the results obtained from event study analysis should be interpreted with care. Coutts, Mills and Roberts (1997) suggested that any inferences gained from event studies should be based on the pattern of CARs, given that these tend to be consistent across different estimation periods and sampled firms.

6.7.3 Empirical Results

In conducting the event study, the standard procedure of an OLS market model was used. The market model specified in Equation 6.6 was estimated using data from T-62 to T-3. Table 6.12 shows summary statistics based on the estimation of the market models for the 182 stocks. As may be expected the mean t-ratio for α indicates that most of the estimated coefficients are insignificant, whilst the mean t-ratio for β indicates a highly significant coefficient across stocks.

[57] Relevant studies include Saunder (1980) and Hays and Upton (1986).

Table 6.12: Market Models Estimated through Daily Data – Summary Statistics

	α	*t-ratio:* α	β	*t-ratio:* β	R^2	*Adjusted* R^2
Mean	0.0008	(0.18)	1.2030	(4.66)	0.27	0.26
Median	0.0009	(0.20)	1.2231	(4.71)	0.28	0.26
Std. Deviation	0.0041	(0.89)	0.4433	(1.70)	0.13	0.13
Minimum	-0.0118	(-2.44)	0.1952	(0.82)	0.012	-0.005
Maximum	0.0168	(3.37)	2.6905	(9.09)	0.59	0.58

The summary statistics were compiled on the basis of the 182 market model estimations relating to the individual stocks. Columns 2 to 5 show summary statistics for estimated *alphas* and *betas*, and respective t-ratios. [For instance, the α coefficient across the individual market models had a mean of 0.008; on average the t-ratios relating to α were 0.18; etc.] Columns 6 and 7 show the R-squared and Adjusted R-squared summary statistics of the estimated market models.

Table 6.13: Diagnostic Checks on Estimated Market Models

	Mean	Min.	Max.	95% CV	#	%
F-statistic – F (1,58)	24.6409	0.6785	82.5571	4.0000	169	93%
Order 1 Serial Correlation Test – $\chi^2(1)$	2.2013	0.0004	23.3566	3.8410	36	20%
Order 1 Serial Correlation Test – F (1,57)	2.3897	0.0004	36.3318	4.0000	36	20%
Functional Form Test – $\chi^2(1)$	1.3581	0.0000	16.2858	3.8410	21	12%
Functional Form Test – F (1,57)	1.4317	0.0000	21.2354	4.0000	21	12%
Normality Test – $\chi^2(2)$	76.9884	0.0118	6645.50	5.9910	93	51%
Heteroscedasticity Test – $\chi^2(1)$	1.2330	0.0004	36.3735	3.8410	13	7%
Heteroscedasticity Test – F (1,58)	1.6615	0.0004	89.2925	4.0000	13	7%
Predictive Failure (Chow's Second) Test – $\chi^2(18)$	20.3890	1.8388	295.5171	28.8690	24	13%
Predictive Failure (Chow's Second) Test – F (18,58)	1.0631	0.1022	10.6618	1.8100	23	13%
Chow's First Test – $\chi^2(2)$	1.9924	0.0080	13.5089	5.9910	13	7%
Chow's First Test – F (2,74)	0.9962	0.0040	6.7545	3.1200	13	7%

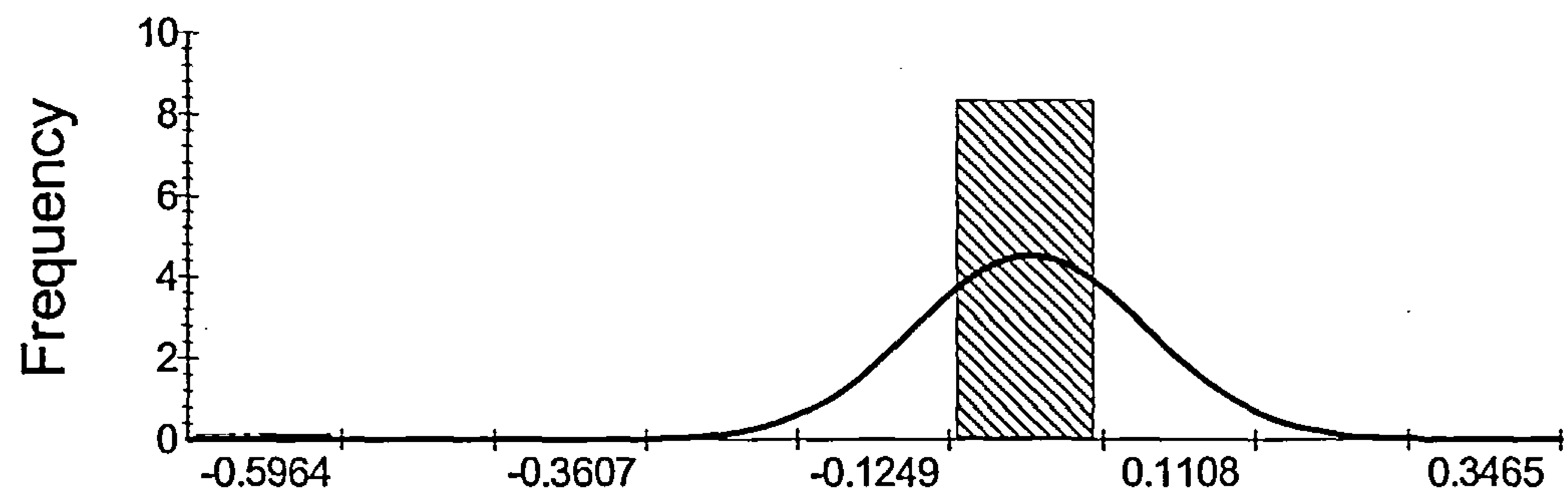
The first column lists the diagnostic test undertaken, whilst the second, third and fourth columns show the mean, minimum and maximum values of the test statistic across the 182 estimated regressions. The fifth column shows the 95% critical value. The number and percentage of stocks where the null hypothesis was rejected at the 95% level of confidence are shown in columns 6 and 7.

The following references relate to the above tests:
Serial Correlation: Breusch and Pagan (1980), Kiviet (1986).
Functional Form Tests: Ramsey (1969)
Normality Test: Jarque and Bera (1980)
Chow's Tests: Chow (1960)

Given that the market model is an integral part of calculating abnormal returns, diagnostic checks on the estimated regression were done. A summary of these tests is shown in Table 6.13. Tests relating to the overall suitability of the estimated regressions, serial correlation, normality and heteroskedasticity of error terms were considered. Both LM and F versions of the tests were conducted, and in all cases the respective versions yielded the same overall inferences. The F-ratio shows that for the large majority of the estimated market models, the regressions have a significant overall fit. This is also confirmed by the Functional Form Test. The Predictive Failure Test and the Chow (1960) Test show that parameters are stable over the sampled period. This is important for the purpose of this study, given that a frequent criticism of event studies is that inferences may be flawed because of time-changing *betas*. These tests indicate that, for most stocks, *betas* were stable over the period which in this case includes the event window, given that 18 out-of sample observations were used for the purpose of these tests. The serial correlation and heteroscedasticity tests do not reject the null hypothesis for the majority of the stocks. The only test where the diagnostics seem problematic is the normality test.

In the test for normality, the null hypothesis of a normal error term distribution is rejected in case of 51% of the stocks. The mean test statistic was 76.99 whilst the median test statistic across stocks was 6.5. The discrepancy between the mean and the median indicates a few abnormally high statistics. In fact, the highest six statistics were as follows: 6645, 2751, 712, 451, 418 and 196. Thus, the mean, minimum and maximum statistics on their own do not provide a clear picture of the test statistic results across stocks, given that the statistics tend to decline considerably after the highest five. Still, the issue of normality merits further consideration. When inspecting the error terms of those stocks with a high statistic, it was noted that the fitted model mimicked the actual market movements reasonably well for most of the time, except in some outlier points. Low log return outliers may be explained by ex-dividend price patterns, given that our definition of returns abstracts from dividend payments. Yet, most of the outliers were high points, and thus the possibility of company announcements is more relevant. These trends resulted in histograms where most of the error terms were close to zero (and therefore almost a uniform distribution) with minimum observations in the tails. The histogram being reproduced in Figure 6.2 shows such a pattern, and it relates to the stock with the highest normality test statistic (CASTROL). These considerations are important, given that whilst one of the standard assumptions underlying the OLS regression model is being violated, at least they instil confidence that the estimated coefficients of the market models are close to their "true values". Therefore, the main objective in dealing with this abnormality should be the enhancement of the power of the significance tests of the abnormal returns, rather than obtaining better estimates of the regression coefficients.

Figure 6.2: Error term histogram for CASTROL with a superimposed normal distribution.



In order to assess the statistical significance of the abnormal returns, one has to compare the error terms in the market model regression throughout the estimation period, to the error terms obtained when using the estimated market model to predict the normal returns during the event window in the absence of the event. The latter errors are assumed to be abnormal returns. In the absence of normally-distributed errors, it is unadvisable to rely on t-ratios or asymptotic test statistics. In addition, according to MacKinnon (2002), for asymptotic tests to be strictly valid, an infinite sample is required. According to this author, bootstrap tests usually perform better than aysmptotic tests for assessing statistical significance and establishing confidence intervals. The advantage of bootstrapping in the present context is that it relies only on the assumption of random sampling from the data at hand, and does not require any distributional assumptions relating to normality or a constant variance.

Given that for the purpose of assessing significance we are interested in the magnitude rather than the direction of the abnormal returns, we may compare the squares of the error terms, in the estimation period to those of the event window for each stock. Yet, when comparing the simple squared residuals for both periods, the summation for the estimation period is likely to be larger, given that we are summing up 60 error terms (emanating from 60 observations) as compared to 18 error terms or abnormal returns (emanating from 18 observations) in the event window. Therefore, prior to taking the square of the error terms in the estimation period, each error has to be divided by 60 and multiplied by 18; or equivalently each error of the event window has to be divided by 18 and multiplied by 60. The latter option was chosen for this study; hence:

$$S.S.R.E_{i,est} = \sum_{t=T-62}^{T-3} \varepsilon_{i,t}^{\ 2} \tag{6.11}$$

and

$$S.S.R.E_{i,event} = \sum_{t=T-2}^{T+15} \left[\frac{60}{18} \varepsilon_{i,t} \right]^2 \tag{6.12}$$

where $S.S.R.E_{i,est}$ and $S.S.R.E_{i,event}$ are the Sum of Squared Rescaled Errors for stock *i*, in the estimation period and in the event window respectively. In inferring whether there are differences in the two groups of *S.S.R.E.*s across stocks, a bootstrap procedure was used. Unbiased market model coefficients as noted through the diagnostic checks shown in Table 6.13, together with the inherent advantages of the bootstrap procedure should enable the correct inference of statistical significance.

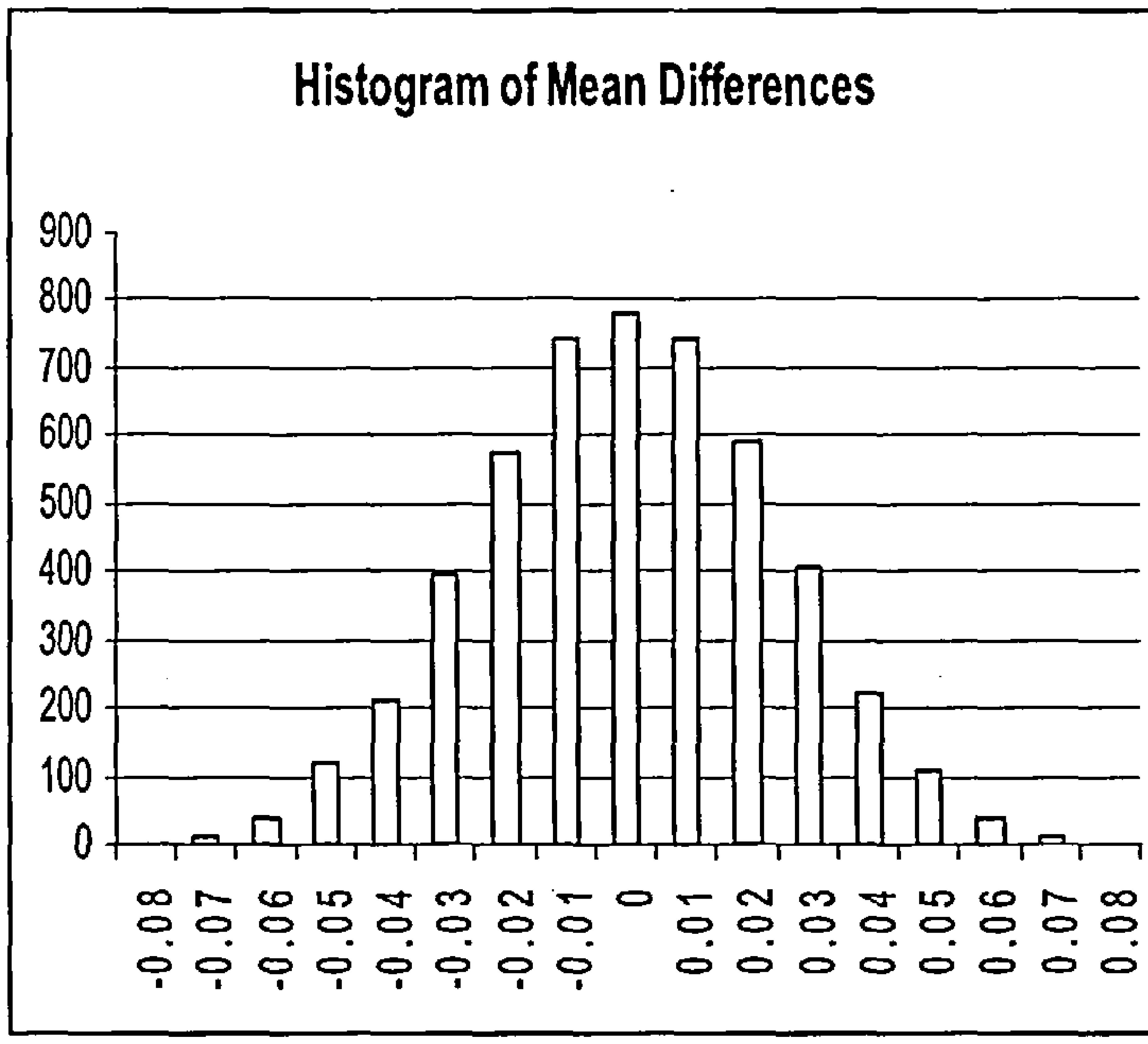
The mean $S.S.R.E_{est}$ was 0.0787 whilst the mean $S.S.R.E_{event}$ was 0.2429; a mean difference of 0.16419. In inferring whether the latter difference is significant or otherwise, we are asking whether this difference could have occurred by pure coincidence. In order to check the probability that the 0.16419 mean difference arose by coincidence, the *S.S.R.E.s* for all stocks in the estimation period and in the event period, were shuffled and combined in a single sample of 364 *S.S.R.E.s*. Observations were then randomly drawn without replacement from this population, creating two sub-samples, each having 182 observations. The difference between means of these two sub-samples was recorded, and the population was re-shuffled. This procedure was repeated 5,000 times.[58] A summary of the mean differences obtained for each procedure is shown in Figure 6.3. No mean differences equal to or higher than 0.16419 were noted, and this implies that the p-value related to the rejection of the null hypothesis that the mean difference was due to coincidence, is less than 0.0002. Therefore we may reject the null hypothesis of equal means (at least) at the 99.98% confidence level.

Having established that the abnormal returns during the event window are significant, we now look at the CARs pattern. For this purpose, the calendar day abnormal returns over the event window were converted to trading day returns, as shown in Equation 6.8. A plot of CARs over the event window is shown in Figure 6.4.[59]

[58] The software routine used for this process is shown in Appendix 6.4.
[59] One potential limitation of this approach is that the concentration of annual reports of Indian companies in the pre-event window may bias the CARs pattern. Given that data on companies' earnings announcements were not available, those sampled securities which went ex-dividend during the pre-event period or during the event window, were searched for as an approximation. The original CARs pattern was re-estimated, omitting those

Figure 6.3: Mean Differences for S.S.M.E. Random Sub-Samples in the Bootstrap Procedure.

Bin Centre	Frequency
-0.08	2
-0.07	11
-0.06	37
-0.05	121
-0.04	214
-0.03	397
-0.02	573
-0.01	743
0	780
0.01	743
0.02	589
0.03	407
0.04	222
0.05	109
0.06	39
0.07	11
0.08	2



This histogram shows a summary of the mean differences obtained when the estimation period and event window *S.S.M.E.s* were randomly re-sampled for 5000 successive times. Each bin covers all values within 0.005 of its centre.

As a "robustness check" on the overall shape of the CARs shown in Figure 6.4, each stock was randomly assigned to one of five sub-samples, as detailed in Appendix 6.5. Three of the latter sub-samples consisted of 36 stocks, whilst the other two, included 37 stocks. For each sub-sample, the abnormal returns were averaged across stocks, and then summed across trading days. The plots of these five sub-samples shown in Figure 6.5 are acceptably similar: CARs start from negative or close to zero, and drift slightly upwards till T+3. The CARs then start to decrease till around T+9 and then drift upwards again. This provides an indication that the overall behaviour of CARs is following a similar pattern across stocks.

securities which went ex-dividend during the period of interest. The CARs pattern for the remaining 116 securities confirmed the original one for the whole sample.

Figure 6.4: Cumulative Abnormal Returns during the Event Window

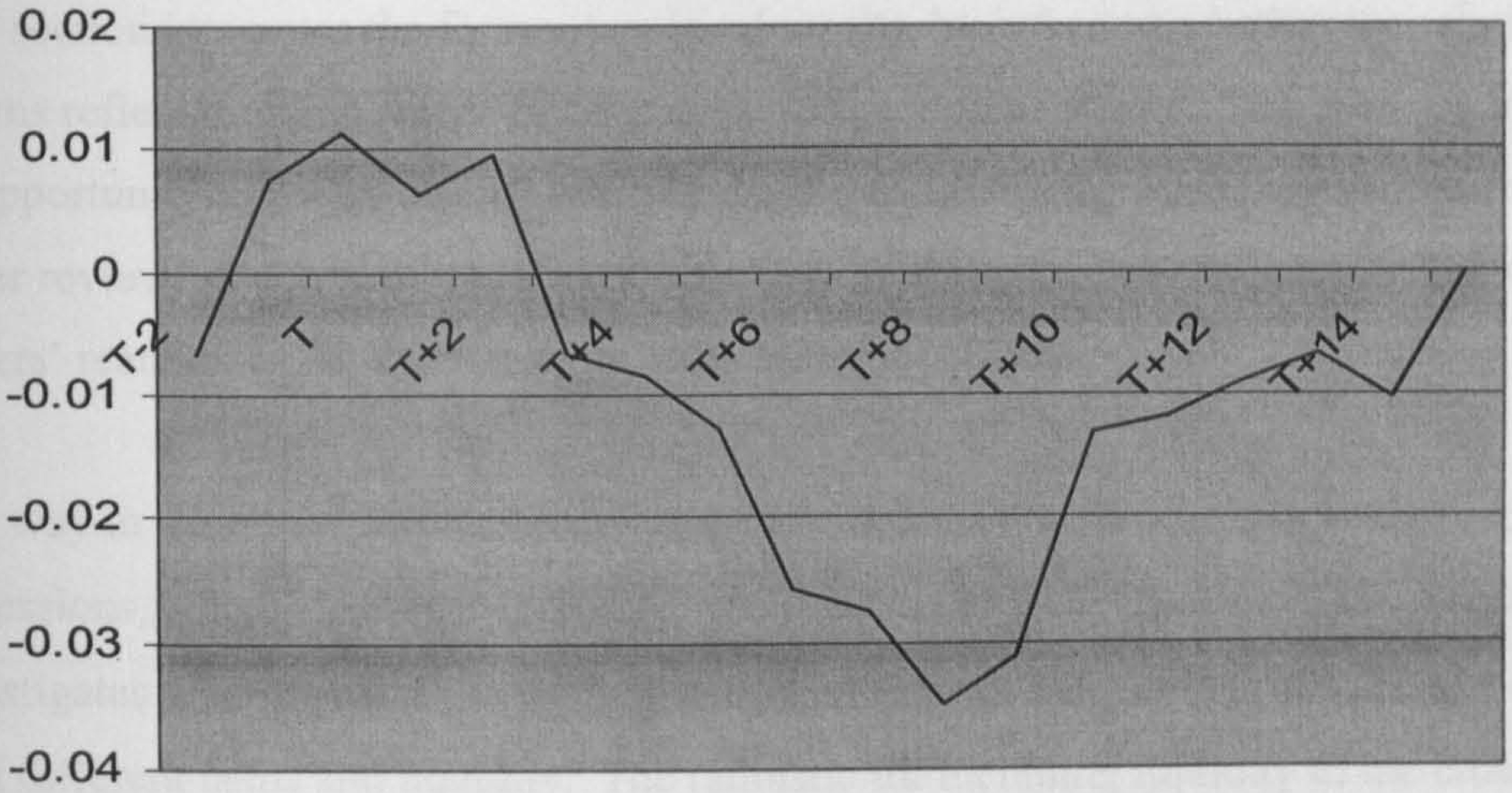
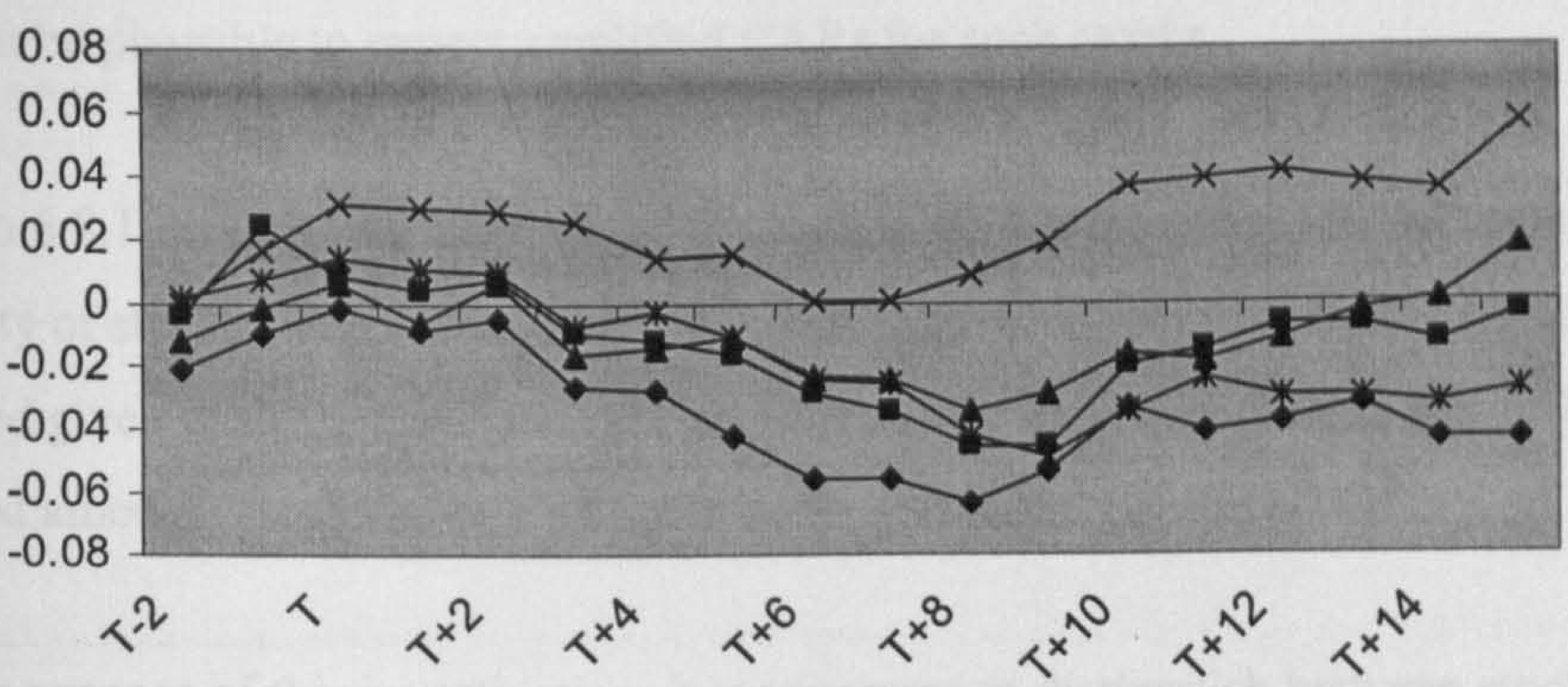


Figure 6.5: Cumulative Abnormal Returns for five Sub-Samples



Overall this section shows that during the event window, stocks experienced significant abnormal returns, in a manner which seems consistent across stocks. Yet, this does not imply that the abnormal returns are significant on theoretical grounds. Whilst the initial and later increasing CARs might correspond to the broad improvement in VEL, the range of negative CARs is harder to reconcile with the VEL changes. Therefore, possible linkages between CARs and VEL changes are considered in the subsequent section.

6.8 Explaining the Abnormal Returns

This section integrates the former empirical results, by inferring whether the relative abnormal returns reflect the changes in VEL for the cross-section of stocks. This exercise also provides an opportunity to "cross check" whether the abnormal returns were the result of the event under review, or due to other unrelated factors. In this way, this section inquires whether the traders' reaction to the event may be considered as justified.

One way in which the above objectives may be achieved is through estimating cross-sectional regressions, where CARs are regressed as a function of VEL changes. This section also investigates whether there were any differing patterns in the changes in VEL amongst stocks with different *betas* and liquidity. The rationale for including liquidity in the cross-sectional regressions explaining CARs rests on the arguments concerning the relationship between stock liquidity and the benefits of auctions (Section 6.2). As for the *betas* of the stocks, one may expect high *beta* stocks to react to a higher degree to general market trends, and therefore it might be plausible to expect amplified CARs for such stocks.

Section 6.8.1 investigates whether the changes in VEL were related to the *betas* and the liquidity of stocks. The subsequent section inquires whether the observed CARs were justified given the VEL changes. The section also investigates whether the CAR patterns differed amongst stocks having different *betas* and initial liquidity.

For the purpose of this investigation, it is necessary to distinguish between stocks by means of dummy variables. The first set of dummy variables denoted by βD relates to the *betas* of the stocks. The dummy variable $\beta D1$ has a value of 1 for stocks with $\beta \leq 0.8$, and zero otherwise. Thus it indicates stocks with a relatively low β. The dummy variable $\beta D2$ has a value of 1 for stocks with $\beta \geq 1.25$, and zero otherwise. Thus it indicates stocks with a relatively high β. These values of *beta* were chosen in a way to obtain an approximately equal number of stocks in the three categories of high, low and average *betas*.

The second set of dummy variables serves as an indicator of liquidity and is denoted by *LD*. The mean volume during the pre-event period, i.e. from T-63 to T-1, was used to specify these dummy variables. The dummy variable *LD1* has a value of 1 for stocks with daily mean volume $\leq$ 40,000 shares, and zero otherwise. It indicates that the stock is relatively less liquid.[60] The dummy variable *LD2* has a value of 1 for stocks with a daily mean volume ≥ 140,000 shares, and zero otherwise. *LD2* indicates a highly liquid stock. Again, these volume values were chosen in such a way to divide the whole sample into three, approximately equal categories.[61]

6.8.1 The Effect of *Betas* and Liquidity on VEL Changes

Eight linear OLS regressions were run, in order to test for relationships between VEL changes *vis-à-vis* the *betas* and initial liquidity of the stocks. Given that the tests of volatility (Section 6.4) gave different results, both SIDP and ORR were regressed on βD and *LD* of the stocks. As for efficiency and liquidity, since the measures showed the same qualitative effect of the auction suspension, only one measure was used as regressand: the percentage change in RRD and the percentage change in the Volume per Unit of Return Ratio.[62]

Table 6.14: Regression Results for Changes in Volatility, Efficiency and Liquidity

Dependent Variable	*Beta* Regressions				Liquidity Regressions			
	Intercept	$\beta D1$	$\beta D2$	R{bar}^{2}	Intercept	LD1	LD2	R{bar}^{2}
% Δ Intra-Day Scaled Difference	-0.1100 (5.29)	0.0165 (0.48)	-0.0067 (0.24)	0.0028 {-0.008}	-0.1163 (5.73)	0.0421 (1.44)	-0.0220 (0.75)	0.0260 {0.0151}
Δ Rev (π)	-0.0162 (0.52)	-0.0721 (1.40)	-0.0490 (1.19)	0.0129 {0.0019}	-0.0427 (1.39)	0.0132 (0.30)	-0.0452 (1.02)	0.0102 {-0.001}
% Δ RRD	-0.1348 (1.16)	0.0929 (0.49)	0.0405 (0.27)	0.0013 {-0.010}	-0.1136 (1.00)	0.1559 (0.95)	-0.1067 (0.65)	0.0138 {0.0028}
% Δ Volume / Return Ratio	0.3737 (2.73)	-0.0715 (0.32)	0.2406 (1.33)	0.0158 {0.0048}	0.4854 (3.65)	0.2496 (1.30)	-0.2950 (1.54)	0.0415 {0.0308}

Column 1 specifies the explanatory variable, which was first regressed as a function of an intercept and β dummies and then as a function of an intercept and liquidity dummies. T-ratios are shown in brackets underneath the coefficient. The R-squared relating to each regression is shown in columns 5 and 9 respectively, while the Adjusted R-squared is shown in braces underneath. Each regression was estimated through 182 observations, comprising the individual stocks.

Regression results are summarised in Table 6.14. None of the dummy variables are significant at the 95% level of confidence, and the regressions have low explanatory power. Therefore, the observed VEL changes seem unrelated to the *betas* or the initial liquidity levels

[60] Given that the chosen sample consists of the most liquid stocks traded on NSE, the term "less liquid" does not necessarily imply "illiquid".

[61] These sub-samples map into Samples A, B and C, referred to in Table 6.3.

[62] The measures were selected on the basis of a higher significance level in the VEL comparisons.

of stocks.[63] Yet, this test indicates that if we include the βD and LD together with VEL changes in a cross section regression to explain CARs (as done below), the regression should not be multicollinear since VEL changes seem unrelated to the dummies.

6.8.2 Explanatory Factors of Cumulative Abnormal Returns

The aim of this section is to explain (trading time) CARs as a function of changes in VEL. Considering the CARs pattern over the event window shown in Figure 6.4, we note that there is an increasing segment and a downward sloping portion. Whilst the magnitude of the abnormal returns is statistically significant, as established in Section 6.7.3, we note that the CARs pattern tends to reverse over time.[64] The final value of CARs across stocks during the event window is very close to zero (but slightly negative at around -0.000064). This presents a problem, in the sense that if we were to regress the CARs noted on the final day of the event window on changes in VEL, the specification may be flawed since it does not make sense to regress the overall (slightly) negative reactions of traders as a function of changes, which generally point at an improvement in the overall market structure.

Given this, six OLS regressions were run:

a) CARs from T+9 till T+15 (upward sloping) were regressed on % changes in VEL factors which showed an improvement. This regression was then repeated twice but βD and LD were respectively included in the estimations.

b) A second set of regressions investigates whether the initial negative reaction (T=0 till T+8) may be explained by the higher volatility as indicated by the overnight return reversal coefficient π. βD and LD were subsequently included in separate regressions.

The results are shown in Table 6.15. As regards the upward sloping CARs regression shown in Panel A, the %Δ in Intra-Day Scaled Difference is significant but in the unexpected direction, the %Δ in RRD is insignificant in the expected direction, whilst the %Δ in Volume Return Ratio is significant in the expected direction. When introducing βD and LD in the regression, these dummy variables are insignificant, even if they add to the explanatory power

[63] The latter result is thus inconsistent with the findings of Kairys, Kruza, and Kumpins (2000a) cited above, who found that increased liquidity largely accrued to the most liquid stocks.

[64] Despite that CARs are statistically significant this does not necessarily imply any overall abnormal change during the event period. Brown and Warner (1980) showed that statistically significant CARs may occasionally be obtained in the absence of any event.

of the first regression. Nonetheless, the β dummy variables are both in the same direction, whereas if the relationship between *betas* and CARs is linear, one would expect that the dummy variable for low β stocks would have a coefficient which is of the opposite sign of that of high β stocks.

The regressions explaining the downward sloping CARs are shown in Table 6.15 Panel B. The intercept is highly significant. The negative CARs may be explained by the increase in Overnight Return Reversals, which is marginally significant at the 90% level of confidence.

Table 6.15: Regressions with CARs as Dependent Variables

Panel A: Upward Sloping CARs

Dependent	Inter.	ΔSD	ΔRRD	ΔV/R	βD1	βD2	LD1	LD2	R^2
CARs T+9 till T+15	0.048 *** (4.15)	0.225 *** (3.80)	-0.001 (0.09)	0.024 *** (2.88)					0.174 {0.160}
CARs T+9 till T+15	0.057 *** (3.54)	0.230 *** (3.87)	-0.001 (0.06)	0.023 *** (2.72)	-0.031 (1.34)	-0.003 (0.17)			0.184 {0.161}
CARs T+9 till T+15	0.046 *** (2.83)	0.216 *** (3.65)	-0.002 (0.16)	0.021 *** (3.54)			0.025 (1.25)	-0.018 (0.89)	0.194 {0.171}

The dependent variable for each regression is shown in the first column, whilst the subsequent columns show the coefficients of the independent variables. Regressors are as follows: Intercept (Inter.), % Δ in Intra Day Scaled Difference (ΔSD), % Δ in RRD (ΔRRD), % Δ in Volume/Return Ratio (ΔV/R), *Beta* Dummy Variables (*βD1* and *βD2)*, and Liquidity Dummy Variables (*LD1* and *LD2)*. T-ratios are shown underneath the respective coefficients in brackets. Statistical significance at the 99%, 95% and 90% levels of confidence is denoted by ***, ** and * respectively. The last column shows the R-Squared of the regression, whilst the Adjusted R-Squared is included in braces underneath. Each regression was estimated through 182 observations, comprising the individual stocks.

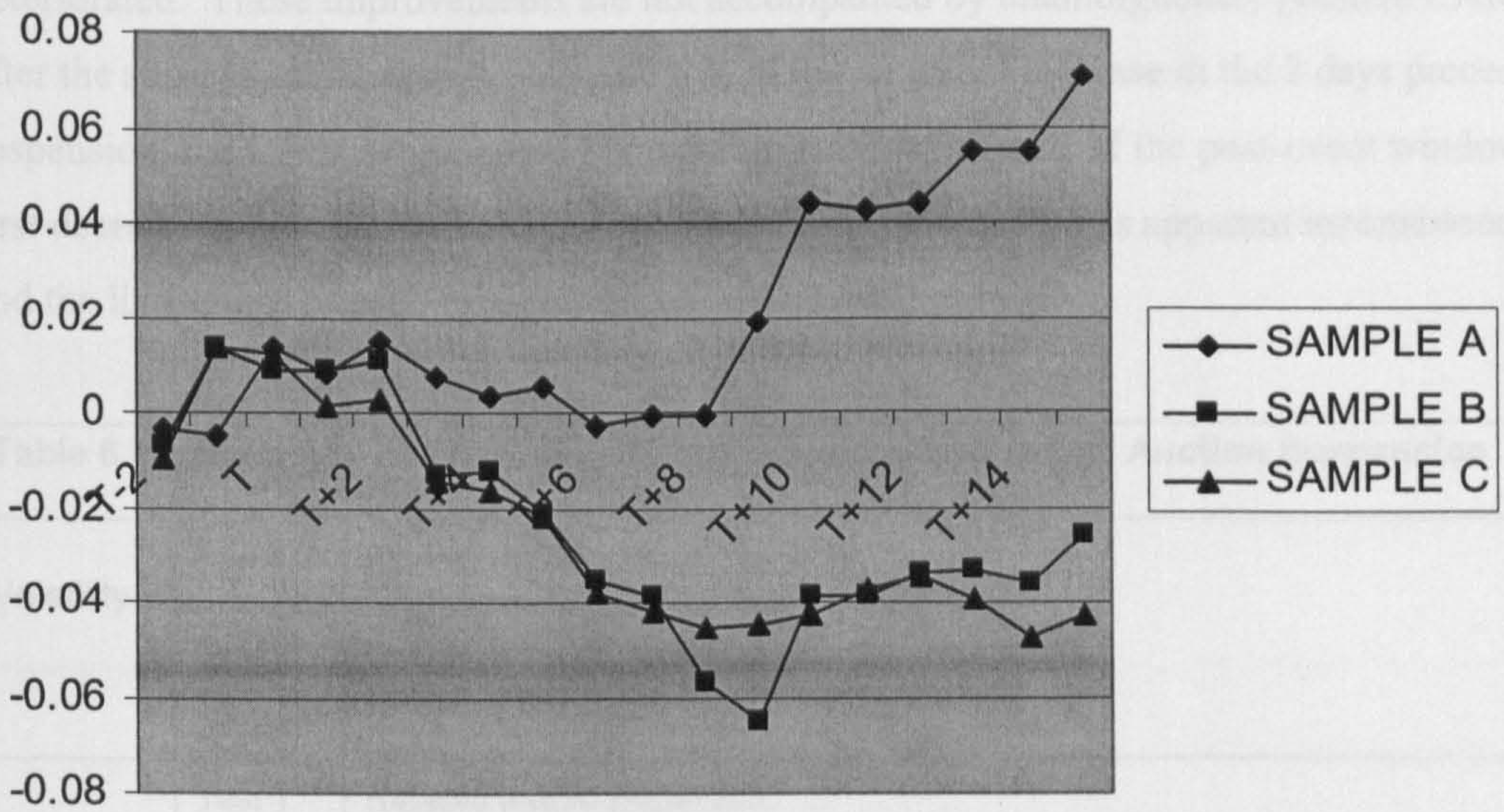
Panel B: Downward Sloping CARs

Dependent	Inter.	ΔOR	βD1	βD2	LD1	LD2	R^2
CARs T+0 till T+8	-0.039*** (4.05)	0.070 * (1.83)					0.018 {0.013}
CARs T+0 till T+8	-0.036** (2.25)	0.070 * (1.80)	0.000 (0.00)	-0.005 (0.25)			0.019 {0.002}
CARs T+0 till T+8	-0.068*** (4.40)	0.063 * (1.69)			0.074*** (3.33)	0.015 (0.67)	0.081 {0.066}

The dependent variable for each regression is shown in the first column, whilst the subsequent columns show the coefficients of the independent variables. Regressors are as follows: Intercept (Inter.), Δ in Overnight Return Reversals (ΔOR), *Beta* Dummy Variables (*βD1* and *βD2)*, and Liquidity Dummy Variables (*LD1* and *LD2)*. T-ratios are shown underneath the coefficients in brackets. Statistical significance at the 99%, 95% and 90% levels of confidence is denoted by ***, ** and * respectively. The last column includes the R-Squared of the regression, whilst the Adjusted R-Squared is shown in braces underneath. Each regression was estimated through 182 observations, comprising the individual stocks.

Another significant coefficient in the "downward sloping portion" regression set is *LD1*, the dummy variable for the relatively less liquid stocks, where the sign indicates that less liquid stocks experienced higher returns. However, as the dummy for the most liquid stocks is also positive but insignificant, one cannot conclude that there is a well-defined relationship between liquidity and the CARs. To check these results, the whole sample of stocks was split into high, medium and less liquid stocks, and the mean CARs were recalculated for each sample as shown in Figure 6.6. The figure visually confirms the overall difference between the CARs of the less liquid stocks (Sample A) and those of medium and high liquidity stocks (Samples B and C). The difference between the CARs of average and highly liquid stocks is not as striking. The reason for this may be due to the original sampling process, where the most liquid stocks traded on NSE were selected. Such a sampling process implies that the Sample A stocks which we are labelling as "less liquid", are in fact "moderately liquid" as compared to the unsampled stocks, whilst Samples B and C might both be "highly liquid".

Figure 6.6: Different CAR patterns for stocks with differing liquidity levels.



Sample A includes those 59 sampled stocks featuring lowest liquidity levels in terms of pre-event daily mean volume. Sample C includes the 59 stocks showing the highest pre-event daily mean volume, whilst the remaining 64 stocks were allocated to Sample B as "average liquidity stocks".

The fact that less liquid stocks experienced higher CARs after suspension, contradicts the argument that less liquid stocks tend to benefit more from call auctions as found in the studies such as Comerton-Forde (1999) and Kairys, Kruza, and Kumpins (2000 a). One possible explanation for this behaviour on part of NSE traders is that the call auction for less liquid stocks was not functioning reasonably well on the grounds that these stocks were not actively traded during the auctions (Table 6.3). These findings provide some support to the arguments of Madhavan and Panchapagesan (2000) and Ellul *et. al.* (2004) that call auction may not be of benefit to less liquid stocks. The latter authors argued that the value of call auctions may be limited by "thick market externalities", in the sense that traders only enter the auction if they believe a sufficient number of other traders will be present so as to establish informationally-efficient prices. The investigation of Comerton-Forde and Rydge (2006 a) offers another notion as to why the auction may have been less suited for less liquid stocks, in the sense that auctions may be used to manipulate prices and manipulation is less costly in illiquid stocks.

6.9 *Further Discussion*

Table 6.16 summarizes the main findings on VEL changes following the auction suspension. Volatility, efficiency and liquidity broadly improved, although one measure of volatility deteriorated. These improvements are not accompanied by unambiguously positive CARs after the suspension, as shown in Figure 6.4. After an initial increase in the 2 days preceding suspension, the CARs are negative for most companies for most of the post-event window: first decreasing then increasing. Five possible explanations for this apparent inconsistency and the limitations of each explanation are considered below.

Table 6.16: Summary of Changes in VEL Factors Following Call Auction Suspension

Volatility	Test 1	Scaled Intra-Day Price Difference (Significant (99%) in favour of suspension)
	Test 2	Overnight Return Reversal (Significant (99%) in favour of auctions)
Efficiency	Test 1	Relative Return Dispersion (Significant (99%) in favour of suspension)
	Test 2	Return Serial Correlation (Insignificant in favour of suspension)
	Test 3	Opening Serial Correlation as proxy for Opening Price Discovery (Significant (99%) in favour of suspension)
Liquidity	Test 1	Number of Shares Transacted (Significant (90%) in favour of suspension)
	Test 2	Volume per Unit of Return (Significant (99%) in favour of suspension)
	Test 3	Time Trend Model (Auction Dummy is significant (99%) in favour of suspension)

Explanation 1:

The contradictory evidence on volatility is interesting, given that the results indicate that intra-day volatility decreased whilst overnight volatility increased. One possible explanation for this might be that the opening auctions were not successful in reducing intra-day volatility, whilst the closing auctions were contributing towards reducing overnight volatility. The latter argument is in line with the empirical study of Pagano and Schwartz (2003) who found that the closing call auction at the (former) Paris Bourse resulted in improvements in the price discovery process.

The statistics presented in Table 6.3 show that the closing call auction is more active than the opening call auction and therefore it might be the case that since around half of the sampled securities do not trade in the morning auction, then the potential benefits from such an auction may not materialize for a large portion of the shares. In addition, when looking at the average number of transactions for the shares in Sample A during the opening auction, one may also question whether such a volume is "robust" enough to ensure that the established price is efficient. These ideas cast doubts over how much effective the opening call auction was in reducing intra-day volatility and increasing pricing efficiency. Yet, it is relevant to point out that this evidence does not disclose a limitation in call auction procedures themselves. It rather suggests that call auctions have to be sufficiently active in order to reap any expected benefits, in line with the observation of Schwartz (2000) that call auctions should attract a "critical mass order flow" since otherwise they may fail.

Existing literature suggests further reasons why the closing auction may have been more effective than the opening one. For instance, Hillion and Suominen (2004) found that closing call auctions may reduce the potential for market participants to manipulate closing prices, whereas the theoretical model of Caillaud and Mezzetti (2004) suggests that some participants might use (or refrain from using) the initial auction to conceal information from other traders.

Explanation 2:

The results could be related directly to the liquidity differences of the shares. As Figure 6.6 shows, CARs realized from T=0 till T+8, for the relatively liquid stocks (Samples B and C) were negative. Less liquid stocks experienced no material CARs. The rationale behind this might be that the less liquid stocks traded much less actively in the call auctions and therefore had little to lose from suspension. However, since the liquid stocks traded more actively during the auctions, the traders reacted negatively, possibly given the forgone expected benefits relating to auctions. This is consistent with the view that higher liquidity stocks did benefit from the call auctions but low liquidity stocks did not.

After T+8, all of the sampled stocks experienced a positive CAR pattern. One possibility is that this may have been related to the overall improvement in VEL factors although Table 6.15 Panel A shows that these changes have little explanatory power on the CARs pattern. It is plausible that the reaction to VEL changes occurred in the late stages of the event window, given that the impacts of market microstructure changes might require more time to evaluate.

Explanation 3:

Given the general improvement in VEL following the auction suspension, one might expect positive CARs over the event window. Yet, this does not seem to be the case with the CARs pattern at hand. Section 6.8.2 indicates that the CARs pattern observed during the event window cannot be convincingly explained by changes in VEL factors. One explanation which may be considered is that the downward sloping part of the CARs in the initial days was an overreaction and the abnormal returns subsequently reversed as a correction, maybe in view of the general VEL improvements. If this is the case, Figure 6.6 shows that the overreaction was confined to the more liquid stocks and this is plausible given that the latter stocks traded more actively in the auction. Despite this, if the upward sloping part of the CARs was indeed a correction, such correction should *not* have occurred in case of less liquid stocks, given that there was no overreaction in these stocks in the first place. Therefore the possibility of an overreaction followed by a correction is not completely supported by the CARs pattern.

Explanation 4:

One possible occurrence is that the improvements in VEL were priced in prior to T=0, even though the suspension was announced on the day of implementation. In fact the event window shows positive CARs in days T-2 and T-1. This may imply insider trading, or that the suspension was expected by the market. The latter is possible because NSE went through a period whereby it was endeavouring to introduce call auctions, but had to suspend them due to software-related problems.[65] However, changes which affect the structure of trading can be difficult to price in fully before the event because these may lead to unexpected changes in

[65] Author's correspondence with Susan Thomas, Assistant Professor at Indira Gandhi Institute of Development Research, Bombay, India.

volume and composition of trading. In addition, if the auctions were suspended due to software glitches on one particular day, the suspension would have been difficult to predict.

Explanation 5:

It is also possible that the call auctions had utility for specific types of investors, especially domestic or foreign institutions which may be key providers of market liquidity at certain times. Thus, the different inferences obtained from the VEL comparisons and the event study might be due to differing reactions of particular trader categories. Available data did not permit a direct test of this hypothesis, but it seems unlikely that call auctions could have benefits for domestic institutions which would not be picked up in the above general tests. During the period covered by this analysis, foreign institutional investors (FIIs) were subject to firm-specific ceilings on the percentage share capital they were permitted to hold in individual Indian companies. Once this ceiling was approached, FIIs were required to dispose of part of their holdings and a liquid market would be essential for this to function smoothly. The call auctions may have facilitated this process – in fact soon after the auctions were suspended, NSE introduced (in December 1999) a new trading segment specifically to enable FIIs to dispose of security holdings in excess of the permitted maxima.

None of these explanations is entirely satisfactory, but together, they do suggest that the call auctions were not as effective as might have been expected, particularly at the opening, and for less liquid stocks.

6.10 Conclusion

This empirical study investigated the effect of the suspension of call auctions on VEL and analysed the stock price reactions to the event. It was noted that the abnormal returns during the event period were significant in terms of their magnitude, and their pattern was robust across different sub-samples of the stocks. Overall, the empirical results suggest an improvement in VEL and no clear-cut market reaction in terms of CARs. In addition, no evidence was found to support the notion that call auctions are particularly effective for trading less liquid stocks, given that when regressing VEL changes over the liquidity dummy variables the latter were insignificant.[66]

To the author's knowledge, this is the first study to compare call auctions and continuous trading following a suspension, where no other changes in market protocols took place. The investigation of such an event in the context of an emerging market is an additional noteworthy factor given that low liquidity is more of a potential problem in such markets as compared to those in the major industrial countries. The main conclusions from the study are summarised underneath.

First, the findings confirm the prevailing wisdom that market microstructure changes do have measurable and significant effects on stock prices and on market performance measures such as volatility, efficiency and liquidity. The results suggest that call auctions do not necessarily enhance VEL factors as discussed *inter alia* by Madhavan (1992). Still, this does not allow us to dismiss the theoretical conclusions of authors such as Economides and Schwartz (1995) predicting more efficient information aggregation in an auction setup, since the adverse impacts of the auctions on VEL found in this study may have been the result of a badly structured auction or a set-up which was inadequate for the underlying NSE characteristics. As noted by Schwartz (2000), a badly structured call auction is likely to fail.

Second, no clear-cut market reaction to the suspension was found. The CARs are significant but initially they decrease and subsequently increase. In particular, the reaction to the auction suspension in case of the most liquid stocks was negative (though this reaction was subsequently reversed). This two-phase reaction across stocks is not wholly unexpected given that market microstructure changes may take longer to evaluate. The cross-sectional relationships between the CARs and the underlying VEL factors are also imprecise. Despite this, stocks which experienced the most improvements in efficiency and liquidity also experienced higher CARs, although the efficiency effect was not significant (Table 6.15). The improvement in intra-day volatility had a positive impact on the cross-section of CARs, while the deterioration in inter-day volatility had the expected negative effect.

Third, one may conjecture that a source of these conflicting findings may lie in the liquidity of the sampled securities. Results point at a difference in the response to the suspension as

[66] One possible explanation for this result is that given that the sample consists of the most liquid stocks, it does not include enough sampling variation in terms of liquidity for the detection of any relationship between liquidity and changes in VEL.

between less liquid stocks and medium and highly liquid stocks. Less liquid stocks traded less in the auctions than other securities, especially at the opening, and they experienced the most gains following the suspension. The results suggest that the less liquid stocks did not benefit from the auction system, and that the closing auction may have been more effective than the opening one. This could be because of a liquidity threshold which stocks have to pass to reap the information benefits of an auction, as outlined by Schwartz (2000) and Ellul, Shin and Tonks (2004). Indeed, following Comerton-Forde and Rydge (2006 a), auction price manipulation is less costly in case of less active securities. A related argument is that the negative evidence surrounding call auctions found in other studies may partly emanate from low call auction activity, rather than a flawed overall structure of auctions. In particular it may not be justified to expect call auctions to contribute to pricing efficiency of less liquid stocks, if the latter fail to trade actively during the auction.

These results have some important general implications.[67] First, the findings support the argument that call auctions are not necessarily a superior method for opening and closing an otherwise continuous market. We cannot support the notion that the main disadvantage of call auctions is that they prohibit stocks from trading continuously given that indications of further disadvantages in terms of VEL were obtained. The initial negative reaction on part of traders upon the suspension of the auction confirms the conjecture that when auctions are held at the opening and at the closing, the restriction from prompt trading is not so pronounced since stocks still trade continuously most of the time. If the auctions were viewed by traders as "a restriction from continuous trading", the former would have been relieved upon the suspension and responded with positive CARs immediately. The benefits or costs of call auctions appear to depend on the composition of the shares being traded. This suggests that future research will need to delve more deeply into the nature of the trading process with a particular reference as to how this may differ across stocks of varying liquidity. Second, the above results show that it cannot be taken for granted that auctions improve share trading in a less liquid emerging market. On the NSE, it appears to have been precisely the less liquid securities which gained least from the auction system.

In interpreting the above results, one should keep in mind that the findings focused on auction effectiveness from the point of view of the market in general as opposed to specific players. Whilst it is reasonable to assume that the design of the trading protocol should reflect the requirements of the general market, the auctions might still have presented particular

[67] A limitation of the analysis is that the software issues prior to suspension may have had an impact on the effectiveness of the auction.

advantages / disadvantages to specific market participants such as large traders. The desirability of call auctions to specific trader categories is an additional issue which may be explored in future research.

Finally, further research is required on the linkages between call auctions and other elements of the trading setup such as price limits, transparency and the role of call auctions in a dealership market. In the absence of such knowledge it remains difficult to assess the desirability of call auctions on particular trading venues – save for experimenting with actual changes in the trading protocol, which might not be an optimal policy.

In view of the contrasting evidence on the impact of the auction suspension on NSE volatility, the subsequent chapter constitutes a more detailed analysis on the volatility changes following the suspension.

APPENDIX 6.1

Final Sample of Individual Stocks

1. Abb
2. Adaniexpo
3. Amarajabat
4. Andhrapet
5. Apollohosp
6. Apollotyre
7. Aptech
8. Arvindmill
9. Ashokley
10. Bajajauto
11. Bankbaroda
12. Bankindia
13. Bankpunjab
14. Bataindia
15. Bauschlomb
16. Bel
17. Bharatforg
18. Bhel
19. Bilt
20. Bindalagro
21. Birlaeric
22. Bomdyeing
23. Bongairefn
24. Bpcl
25. Bpl
26. Britannia
27. Bses
28. Cadbury
29. Carrierair
30. Castrol
31. Ceat
32. Centurytex
33. Cmc
34. Coatviyela
35. Cochinrefn
36. Colgate
37. Corpbank
38. Crestcomm
39. Crompgreav
40. Dabur
41. Dclpoly
42. Dcmdaewoo
43. Digitaleqp
44. Dlfcement
45. Drreddy
46. Emerck
47. Escorts
48. Essarship
49. Esselpack
50. Finpipe
51. Fujitsicim
52. Germanrem
53. Glaxo
54. Gnfc
55. Godrejsop
56. Gramophone
57. Grasim
58. Gujambcem
59. Gujratgas
60. Gujsidhcem
61. Hcl-Hp
62. Hdfcbank
63. Herohonda
64. Himachlfut
65. HindalcO
66. Hindevelop
67. Hindlevchm
68. Hindlever
69. Hindmotor
70. Hindpetro
71. Hindzinc
72. Hocl
73. Hoteleela
74. Icici
75. Icicibank
76. Idbi
77. Indal
78. Indhotel
79. Indiacem
80. Indogulf
81. Indrayon
82. Infotecent
83. Ingerrand
84. Insilco
85. Ioc
86. Ipcalab
87. Ipcl
88. Itc
89. Iti
90. Itil
91. Jct
92. Jindvijstl
93. Jpind
94. Kecintl
95. Kesoramind
96. Kopran
97. Krebsbio
98. Kronecomm
99. L&T
100. Lakme
101. Laneseda
102. Leadedsys
103. Lichsgfin
104. Lml
105. M&M
106. Madrasrefn
107. Mahaintl
108. Mastershar
109. Mastgain92
110. Mastplus91
111. Max
112. Mcdowell
113. Mircelectr
114. Moserbaer
115. Mrf
116. Mtnl
117. Nagarfert
118. Nelco
119. Nepcmicon
120. Nestle
121. Niit
122. Nilkamplst
123. Nirma
124. Nocil
125. Novartis
126. Orientbank
127. P&G
128. Padminpoly
129. Parkedavis
130. Peerleship
131. Pennaralum
132. Pentfrprod
133. Pfizer
134. Philips
135. Psidatasys
136. Punjabtrac
137. Raincalcin
138. Ramanewspr
139. Raslamipak
140. Raymond
141. Reckcolman
142. Relcapital
143. Reliance
144. Rhonepouln
145. Rolta
146. Sail
147. Saloraintl
148. Samtel
149. Sanghipoly
150. Sbin
151. Shasunchem
152. Shyamtele
153. Silverline
154. Smithklpha
155. Smitklbech
156. Softsolint
157. Spic
158. Spicelec
159. Spicfine
160. Sqrdsfware
161. Srf
162. Sterlite
163. Sunpharma
164. Suppetro
165. Surajdiamn
166. Tatachem
167. Tataelxsi
168. Tatafin
169. Tatapower
170. Tatatea
171. Tatavashis
172. Telco
173. Thomascook
174. Tisco
175. Tvselec
176. Unitedphos
177. Ushabeltro
178. Utibank
179. Vdoconintl
180. Vikaswsp
181. Voltas
182. Wartdeisel

APPENDIX 6.2

A Summary of the Data Periods Used for the Comparison Analysis and Event Study.

Pre-Event and post-Event periods used for the comparison analysis								
	First day		Last day		Number of days in period			
	Event Time	Date	Event Time	Date	Open days	Closed days*	Week-days	Total days
Pre-Event period**	T-62	3rd March 1999	T-1	8th June 1999	62	8	70	98
Post-Event period**	T+1	10th June 1999	T+62	3rd Sept. 1999	62	0	62	86

Estimation period and event window used for the event study								
Period	First day		Last day		Number of days in period			
	Event Time	Date	Event Time	Date	Open days	Closed days*	Week-days	Total days
Estimation Period	T-62	3rd March 1999	T-3	4th June 1999	60	8	68	94
Event Window	T-2	7th June 1999	T+15	30th June 1999	18	0	18	24

* Excluding Weekends

** When working with intra-day prices, rather than returns, one further observation was available and therefore data from T-63 till T-1 were used for the pre-event period and data from T+1 till T+63 were used for the post event period.

APPENDIX 6.3

First Order Serial Correlations

The name of the stock is shown in Column A; Columns B1, C1 and D1 show pre-event data, whilst post-event data are shown in Columns B2, C2, and D2. The first order serial correlation is shown in Columns B1 and B2. Significance at the 95% level of confidence is denoted by **. In all cases, the standard error is equal to 0.127. The Box-Pierce (1970) statistics are reported in Columns C1 and C2, whilst the Ljung-Box (1978) statistics are shown in Columns D1 and D2. The probability of falsely rejecting the null hypothesis of no serial correlation is shown in square brackets.

A STOCK	B1 COEFF. (pre)	C1 BOX-PIERCE (pre)	D1 LJUNG-BOX (pre)	B2 COEFF. (post)	C2 BOX-PIERCE (post)	D2 LJUNG-BOX (post)
ABB	0.103	0.663 [.415]	0.696 [.404]	0.094	0.549 [.459]	0.576 [.448]
ADANIEXPO	-0.085	0.449 [.503]	0.471 [.493]	-0.215	2.874 [.090]	3.015 [.082]
AMARAJABAT	-0.155	1.496 [.221]	1.569 [.210]	0.202	2.539 [.111]	2.664 [.103]
ANDHRAPET	-0.358**	7.957 [.005]	8.348 [.004]	-0.139	1.198 [.274]	1.257 [.262]
APOLLOHOSP	0.352**	7.670 [.006]	8.047 [.005]	0.161	1.600 [.206]	1.679 [.195]
APOLLOTYRE	0.076	0.354 [.552]	0.372 [.542]	0.279**	4.825 [.028]	5.063 [.024]
APTECH	-0.083	0.423 [.516]	0.444 [.505]	-0.084	0.436 [.509]	0.458 [.499]
ARVINDMILL	0.087	0.474 [.491]	0.497 [.481]	0.163	1.653 [.199]	1.734 [.188]
ASHOKLEY	0.17	1.800 [.180]	1.889 [.169]	0.138	1.186 [.276]	1.245 [.265]
BAJAJAUTO	-0.108	0.717 [.397]	0.752 [.386]	-0.285**	5.022 [.025]	5.269 [.022]
BANKBARODA	0.294**	5.342 [.021]	5.604 [.018]	0.183	2.066 [.151]	2.168 [.141]
BANKINDIA	0.139	1.198 [.274]	1.257 [.262]	-0.032	0.062 [.804]	0.065 [.799]
BANKPUNJAB	-0.07	0.304 [.581]	0.319 [.572]	-0.036	0.079 [.778]	0.083 [.773]
BATAINDIA	-0.04	0.101 [.750]	0.106 [.745]	0.141	1.231 [.267]	1.291 [.256]
BAUSCHLOMB	0.141	1.240 [.265]	1.301 [.254]	0.155	1.490 [.222]	1.564 [.211]
BEL	-0.111	0.767 [.381]	0.805 [.370]	0.232	3.329 [.068]	3.493 [.062]
BHARATFORG	-0.096	0.573 [.449]	0.601 [.438]	-0.113	0.794 [.373]	0.833 [.362]
BHEL	0.122	0.917 [.338]	0.962 [.327]	0.118	0.858 [.354]	0.900 [.343]
BILT	0.015	0.014 [.907]	0.014 [.905]	0.232	3.327 [.068]	3.491 [.062]
BINDALAGRO	-0.178	1.962 [.161]	2.059 [.151]	-0.061	0.231 [.631]	0.242 [.623]
BIRLAERIC	0.112	0.772 [.380]	0.810 [.368]	0.033	0.069 [.793]	0.072 [.788]
BOMDYEING	0.054	0.183 [.669]	0.192 [.661]	0.073	0.329 [.566]	0.345 [.557]
BONGAIREFN	-0.246	3.738 [.053]	3.922 [.048]	0.016	0.016 [.899]	0.017 [.897]
BPCL	0.21	2.734 [.098]	2.869 [.090]	-0.02	0.026 [.873]	0.027 [.870]
BPL	0.168	1.743 [.187]	1.829 [.176]	-0.098	0.593 [.441]	0.622 [.430]
BRITANNIA	0.104	0.668 [.414]	0.701 [.402]	0.209	2.703 [.100]	2.836 [.092]
BSES	0.105	0.680 [.410]	0.713 [.398]	0.089	0.492 [.483]	0.517 [.472]
CADBURY	-0.108	0.724 [.395]	0.759 [.384]	-0.189	2.220 [.136]	2.329 [.127]
CARRIERAIR	-0.127	0.992 [.319]	1.041 [.308]	-0.176	1.931 [.165]	2.026 [.155]
CASTROL	0.003	0.001 [.979]	0.001 [.978]	-0.049	0.150 [.699]	0.157 [.692]
CEAT	-0.227	3.189 [.074]	3.346 [.067]	0.125	0.974 [.324]	1.022 [.312]
CENTURYTEX	0.327**	6.637 [.010]	6.964 [.008]	0.123	0.939 [.332]	0.985 [.321]
CMC	0.341**	7.223 [.007]	7.578 [.006]	-0.089	0.489 [.484]	0.513 [.474]
COATVIYELA	-0.004	0.001 [.972]	0.001 [.971]	0.256**	4.060 [.044]	4.259 [.039]
COCHINREFN	-0.083	0.430 [.512]	0.451 [.502]	-0.066	0.271 [.603]	0.284 [.594]

... continued overleaf

A STOCK	B1 COEFF. (pre)	C1 BOX-PIERCE (pre)	D1 LJUNG-BOX (pre)	B2 COEFF. (post)	C2 BOX-PIERCE (post)	D2 LJUNG-BOX (post)
COLGATE	-0.208	2.671 [.102]	2.803 [.094]	0.2	2.482 [.115]	2.604 [.107]
CORPBANK	0.218	2.959 [.085]	3.105 [.078]	0.116	0.828 [.363]	0.869 [.351]
CRESTCOMM	0.041	0.105 [.745]	0.111 [.739]	0.275**	4.704 [.030]	4.935 [.026]
CROMPGREAV	0.018	0.020 [.888]	0.021 [.885]	0.189	2.225 [.136]	2.334 [.127]
DABUR	-0.18	2.007 [.157]	2.106 [.147]	0.086	0.461 [.497]	0.484 [.487]
DCLPOLY	-0.199	2.447 [.118]	2.568 [.109]	0.11	0.746 [.388]	0.783 [.376]
DCMDAEWOO	-0.096	0.568 [.451]	0.596 [.440]	0.231	3.313 [.069]	3.476 [.062]
DIGITALEQP	0.123	0.934 [.334]	0.980 [.322]	0.046	0.134 [.715]	0.140 [.708]
DLFCEMENT	0.131	1.065 [.302]	1.118 [.290]	-0.081	0.403 [.526]	0.423 [.516]
DRREDDY	-0.115	0.819 [.366]	0.859 [.354]	0.241	3.599 [.058]	3.776 [.052]
EMERCK	-0.2	2.487 [.115]	2.609 [.106]	0.024	0.036 [.849]	0.038 [.845]
ESCORTS	-0.068	0.287 [.592]	0.301 [.583]	-0.03	0.056 [.813]	0.059 [.809]
ESSARSHIP	-0.414**	10.62 [.001]	11.14 [.001]	0.023	0.034 [.853]	0.036 [.850]
ESSELPACK	-0.285**	5.046 [.025]	5.294 [.021]	0.223	3.088 [.079]	3.240 [.072]
FINPIPE	0.015	0.014 [.905]	0.015 [.903]	0.061	0.228 [.633]	0.239 [.625]
FUJITSICIM	0.075	0.347 [.556]	0.364 [.546]	0.023	0.032 [.858]	0.033 [.855]
GERMANREM	-0.287**	5.118 [.024]	5.370 [.020]	0.015	0.014 [.906]	0.015 [.904]
GLAXO	-0.195	2.353 [.125]	2.469 [.116]	-0.088	0.482 [.488]	0.505 [.477]
GNFC	-0.107	0.715 [.398]	0.750 [.386]	0.272**	4.573 [.032]	4.798 [.028]
GODREJSOP	0.158	1.543 [.214]	1.619 [.203]	0.171	1.807 [.179]	1.896 [.169]
GRAMOPHONE	0.271**	4.561 [.033]	4.786 [.029]	0.337**	7.032 [.008]	7.378 [.007]
GRASIM	0.037	0.085 [.771]	0.089 [.765]	0.417**	10.80 [.001]	11.32 [.001]
GUJAMBCEM	-0.343**	7.291 [.007]	7.650 [.006]	0.139	1.203 [.273]	1.262 [.261]
GUJRATGAS	-0.003	0.001 [.981]	0.001 [.980]	0.343**	7.276 [.007]	7.634 [.006]
GUJSIDHCEM	-0.205	2.618 [.106]	2.747 [.097]	-0.105	0.684 [.408]	0.717 [.397]
HCL-HP	-0.03	0.057 [.812]	0.060 [.807]	0.169	1.780 [.182]	1.868 [.172]
HDFCBANK	0.008	0.004 [.947]	0.005 [.946]	-0.038	0.089 [.765]	0.094 [.759]
HEROHONDA	-0.236	3.443 [.064]	3.613 [.057]	0.125	0.968 [.325]	1.015 [.314]
HIMACHLFUT	0.184	2.098 [.148]	2.201 [.138]	0.171	1.809 [.179]	1.898 [.168]
HINDALCO	0.134	1.106 [.293]	1.160 [.281]	0.142	1.248 [.264]	1.310 [.252]
HINDEVELOP	-0.215	2.862 [.091]	3.003 [.083]	0.262**	4.259 [.039]	4.468 [.035]
HINDLEVCHM	-0.083	0.431 [.512]	0.452 [.501]	0.193	2.300 [.129]	2.413 [.120]
HINDLEVER	-0.049	0.149 [.700]	0.156 [.693]	0.301**	5.629 [.018]	5.905 [.015]
HINDMOTOR	-0.282**	4.930 [.026]	5.173 [.023]	0.001	0.000 [.993]	0.000 [.993]
HINDPETRO	0.194	2.335 [.127]	2.450 [.118]	0.305**	5.766 [.016]	6.050 [.014]
HINDZINC	-0.113	0.795 [.373]	0.834 [.361]	0.330**	6.744 [.009]	7.075 [.008]
HOCL	-0.028	0.050 [.824]	0.052 [.819]	-0.069	0.296 [.586]	0.311 [.577]
HOTELEELA	-0.001	0.000 [.997]	0.000 [.997]	-0.025	0.038 [.845]	0.040 [.842]
ICICI	0.097	0.579 [.447]	0.608 [.436]	0.185	2.129 [.145]	2.234 [.135]
ICICIBANK	-0.014	0.012 [.914]	0.012 [.912]	-0.208	2.681 [.102]	2.813 [.094]
IDBI	0.079	0.386 [.534]	0.405 [.525]	0.042	0.112 [.738]	0.117 [.732]
INDAL	-0.045	0.126 [.723]	0.132 [.716]	0.462**	13.21 [.000]	13.86 [.000]
INDHOTEL	0.016	0.015 [.902]	0.016 [.900]	0.24	3.562 [.059]	3.737 [.053]
INDIACEM	0.077	0.364 [.547]	0.381 [.537]	0.196	2.376 [.123]	2.493 [.114]
INDOGULF	0.211	2.754 [.097]	2.889 [.089]	0.113	0.795 [.373]	0.834 [.361]
INDRAYON	0.233	3.353 [.067]	3.518 [.061]	0.177	1.943 [.163]	2.039 [.153]
INFOTECENT	-0.011	0.008 [.929]	0.008 [.928]	0.152	1.429 [.232]	1.499 [.221]
INGERRAND	-0.208	2.684 [.101]	2.816 [.093]	-0.014	0.012 [.914]	0.012 [.912]
INSILCO	0.054	0.179 [.673]	0.187 [.665]	0.158	1.548 [.213]	1.625 [.202]
IOC	0.001	0.000 [.991]	0.000 [.990]	0.167	1.738 [.187]	1.824 [.177]

... continued overleaf

A STOCK	B1 COEFF. (pre)	C1 BOX-PIERCE (pre)	D1 LJUNG-BOX (pre)	B2 COEFF. (post)	C2 BOX-PIERCE (post)	D2 LJUNG-BOX (post)
IPCALAB	-0.003	0.001 [.981]	0.001 [.980]	0.309**	5.923 [.015]	6.215 [.013]
IPCL	-0.054	0.180 [.671]	0.189 [.664]	0.056	0.195 [.659]	0.204 [.651]
ITC	-0.262**	4.248 [.039]	4.457 [.035]	-0.147	1.337 [.248]	1.403 [.236]
ITI	-0.255**	4.026 [.045]	4.224 [.040]	0.161	1.602 [.206]	1.681 [.195]
ITIL	0.198	2.439 [.118]	2.559 [.110]	-0.155	1.496 [.221]	1.570 [.210]
JCT	-0.037	0.083 [.774]	0.087 [.768]	-0.114	0.812 [.367]	0.852 [.356]
JINDVIJSTL	-0.222	3.051 [.081]	3.201 [.074]	0.243	3.652 [.056]	3.832 [.050]
JPIND	-0.192	2.283 [.131]	2.396 [.122]	0.277**	4.759 [.029]	4.993 [.025]
KECINTL	0.067	0.276 [.600]	0.289 [.591]	0.239	3.554 [.059]	3.729 [.053]
KESORAMIND	-0.061	0.227 [.633]	0.239 [.625]	0.346**	7.418 [.006]	7.783 [.005]
KOPRAN	0.062	0.237 [.626]	0.249 [.618]	0.083	0.424 [.515]	0.445 [.505]
KREBSBIO	0.02	0.025 [.875]	0.026 [.872]	0.211	2.762 [.097]	2.897 [.089]
KRONECOMM	0.229	3.237 [.072]	3.396 [.065]	0.086	0.461 [.497]	0.484 [.487]
L&T	-0.01	0.006 [.939]	0.006 [.937]	-0.105	0.684 [.408]	0.718 [.397]
LAKME	0.178	1.963 [.161]	2.060 [.151]	0.145	1.295 [.255]	1.359 [.244]
LANESEDA	-0.345**	7.398 [.007]	7.762 [.005]	-0.239	3.544 [.060]	3.718 [.054]
LEADEDSYS	0.05	0.157 [.692]	0.165 [.685]	0.17	1.788 [.181]	1.876 [.171]
LICHSGFIN	0.013	0.011 [.918]	0.011 [.916]	0.146	1.316 [.251]	1.380 [.240]
LML	-0.159	1.574 [.210]	1.651 [.199]	-0.055	0.189 [.664]	0.198 [.656]
M&M	-0.102	0.642 [.423]	0.673 [.412]	0.179	1.976 [.160]	2.073 [.150]
MADRASREFN	-0.12	0.898 [.343]	0.942 [.332]	0.045	0.125 [.724]	0.131 [.717]
MAHAINTL	0.039	0.095 [.757]	0.100 [.752]	0.045	0.124 [.724]	0.130 [.718]
MASTERSHAR	-0.198	2.441 [.118]	2.561 [.110]	-0.142	1.253 [.263]	1.314 [.252]
MASTGAIN92	-0.263**	4.289 [.038]	4.499 [.034]	0.055	0.187 [.666]	0.196 [.658]
MASTPLUS91	-0.042	0.109 [.741]	0.115 [.735]	0.105	0.686 [.408]	0.719 [.396]
MAX	0.075	0.347 [.556]	0.364 [.546]	0.018	0.020 [.887]	0.021 [.884]
MCDOWELL	0.503**	15.70 [.000]	16.47 [.000]	0.142	1.244 [.265]	1.305 [.253]
MIRCELECTR	0.045	0.125 [.724]	0.131 [.717]	0.383**	9.077 [.003]	9.523 [.002]
MOSERBAER	0.15	1.399 [.237]	1.468 [.226]	0.055	0.190 [.663]	0.199 [.656]
MRF	0.023	0.033 [.855]	0.035 [.851]	0.187	2.168 [.141]	2.274 [.132]
MTNL	-0.046	0.131 [.717]	0.138 [.711]	0.112	0.781 [.377]	0.820 [.365]
NAGARFERT	-0.199	2.463 [.117]	2.584 [.108]	0.088	0.481 [.488]	0.504 [.478]
NELCO	0.324**	6.522 [.011]	6.843 [.009]	0.179	1.985 [.159]	2.082 [.149]
NEPCMICON	-0.315**	6.151 [.013]	6.454 [.011]	-0.283**	4.972 [.026]	5.217 [.022]
NESTLE	-0.275**	4.678 [.031]	4.908 [.027]	-0.15	1.393 [.238]	1.462 [.227]
NIIT	0.012	0.009 [.924]	0.010 [.922]	-0.079	0.384 [.536]	0.403 [.526]
NILKAMPLST	-0.045	0.123 [.726]	0.129 [.719]	0.280**	4.854 [.028]	5.092 [.024]
NIRMA	-0.036	0.081 [.776]	0.085 [.771]	-0.037	0.083 [.773]	0.087 [.768]
NOCIL	0.039	0.096 [.757]	0.101 [.751]	0.034	0.074 [.786]	0.077 [.781]
NOVARTIS	-0.078	0.376 [.540]	0.395 [.530]	0.224	3.106 [.078]	3.259 [.071]
ORIENTBANK	0.2	2.487 [.115]	2.609 [.106]	0.063	0.243 [.622]	0.255 [.614]
P&G	-0.109	0.738 [.390]	0.774 [.379]	-0.01	0.006 [.936]	0.007 [.934]
PADMINPOLY	-0.072	0.319 [.572]	0.335 [.563]	0.177	1.953 [.162]	2.049 [.152]
PARKEDAVIS	-0.214	2.835 [.092]	2.975 [.085]	0.068	0.286 [.593]	0.300 [.584]
PEERLESHIP	-0.251	3.918 [.048]	4.111 [.043]	0.003	0.001 [.982]	0.001 [.981]
PENNARALUM	-0.226	3.164 [.075]	3.319 [.068]	-0.243	3.648 [.056]	3.827 [.050]
PENTFRPROD	-0.02	0.024 [.877]	0.025 [.874]	-0.041	0.105 [.746]	0.110 [.740]
PFIZER	0.171	1.803 [.179]	1.892 [.169]	0.21	2.733 [.098]	2.868 [.090]
PHILIPS	-0.057	0.203 [.653]	0.213 [.645]	0.062	0.237 [.626]	0.248 [.618]
PSIDATASYS	0.086	0.457 [.499]	0.479 [.489]	-0.043	0.113 [.737]	0.118 [.731]

... continued overleaf

A STOCK	B1 COEFF. (pre)	C1 BOX-PIERCE (pre)	D1 LJUNG-BOX (pre)	B2 COEFF. (post)	C2 BOX-PIERCE (post)	D2 LJUNG-BOX (post)
PUNJABTRAC	0.212	2.787 [.095]	2.924 [.087]	-0.121	0.907 [.341]	0.952 [.329]
RAINCALCIN	-0.188	2.193 [.139]	2.301 [.129]	0.015	0.013 [.908]	0.014 [.906]
RAMANEWSPR	-0.139	1.192 [.275]	1.250 [.263]	-0.033	0.067 [.796]	0.070 [.791]
RASLAMIPAK	-0.2	2.476 [.116]	2.598 [.107]	0.097	0.586 [.444]	0.615 [.433]
RAYMOND	0.129	1.024 [.312]	1.075 [.300]	0.191	2.260 [.133]	2.371 [.124]
RECKCOLMAN	-0.057	0.199 [.655]	0.209 [.648]	-0.092	0.523 [.469]	0.549 [.459]
RELCAPITAL	-0.277**	4.768 [.029]	5.003 [.025]	0.142	1.254 [.263]	1.315 [.251]
RELIANCE	-0.004	0.001 [.977]	0.001 [.977]	0.069	0.292 [.589]	0.307 [.580]
RHONEPOULN	-0.452**	12.66 [.000]	13.28 [.000]	-0.142	1.252 [.263]	1.314 [.252]
ROLTA	0.21	2.725 [.099]	2.859 [.091]	0.1	0.621 [.431]	0.651 [.420]
SAIL	-0.166	1.704 [.192]	1.788 [.181]	0.132	1.079 [.299]	1.133 [.287]
SALORAINTL	0.103	0.660 [.416]	0.693 [.405]	-0.169	1.776 [.183]	1.863 [.172]
SAMTEL	-0.147	1.342 [.247]	1.408 [.235]	0.088	0.482 [.487]	0.506 [.477]
SANGHIPOLY	-0.205	2.607 [.106]	2.736 [.098]	-0.227	3.181 [.075]	3.337 [.068]
SBIN	0.212	2.797 [.094]	2.934 [.087]	-0.037	0.083 [.773]	0.087 [.768]
SHASUNCHEM	0.264**	4.313 [.038]	4.526 [.033]	0.178	1.969 [.161]	2.065 [.151]
SHYAMTELE	-0.189	2.219 [.136]	2.328 [.127]	-0.004	0.001 [.972]	0.001 [.971]
SILVERLINE	0.152	1.433 [.231]	1.504 [.220]	0.004	0.001 [.977]	0.001 [.976]
SMITHKLPHA	-0.008	0.004 [.949]	0.004 [.947]	-0.091	0.516 [.473]	0.541 [.462]
SMITKLBECH	-0.177	1.948 [.163]	2.044 [.153]	0.07	0.306 [.580]	0.321 [.571]
SOFTSOLINT	0.132	1.083 [.298]	1.136 [.286]	0.032	0.063 [.802]	0.066 [.797]
SPIC	-0.08	0.394 [.530]	0.414 [.520]	0.273**	4.631 [.031]	4.858 [.028]
SPICELEC	0.034	0.073 [.787]	0.076 [.782]	0.151	1.405 [.236]	1.474 [.225]
SPICFINE	0.139	1.204 [.273]	1.263 [.261]	0.197	2.406 [.121]	2.524 [.112]
SQRDSFWARE	0.212	2.784 [.095]	2.921 [.087]	0.255**	4.030 [.045]	4.228 [.040]
SRF	-0.321**	6.405 [.011]	6.720 [.010]	0.018	0.020 [.887]	0.021 [.885]
STERLITE	-0.041	0.106 [.745]	0.111 [.739]	0.278**	4.806 [.028]	5.042 [.025]
SUNPHARMA	0.205	2.596 [.107]	2.724 [.099]	0.139	1.204 [.273]	1.263 [.261]
SUPPETRO	-0.144	1.283 [.257]	1.346 [.246]	-0.04	0.098 [.754]	0.103 [.749]
SURAJDIAMN	-0.239	3.542 [.060]	3.716 [.054]	-0.01	0.006 [.937]	0.007 [.935]
TATACHEM	0.039	0.096 [.757]	0.100 [.752]	0.201	2.495 [.114]	2.618 [.106]
TATAELXSI	0.124	0.946 [.331]	0.993 [.319]	-0.041	0.106 [.745]	0.111 [.739]
TATAFIN	-0.097	0.582 [.446]	0.610 [.435]	0.407**	10.29 [.001]	10.80 [.001]
TATAPOWER	0.077	0.371 [.543]	0.389 [.533]	0.243	3.671 [.055]	3.852 [.050]
TATATEA	-0.036	0.078 [.780]	0.082 [.774]	0.1	0.625 [.429]	0.656 [.418]
TATAVASHIS	0.211	2.750 [.097]	2.885 [.089]	0.098	0.601 [.438]	0.630 [.427]
TELCO	-0.073	0.334 [.563]	0.351 [.554]	0.114	0.803 [.370]	0.842 [.359]
THOMASCOOK	0.029	0.053 [.818]	0.056 [.814]	0.001	0.000 [.994]	0.000 [.994]
TISCO	0.06	0.221 [.638]	0.232 [.630]	-0.049	0.152 [.697]	0.159 [.690]
TVSELEC	0.485**	14.61 [.000]	15.33 [.000]	0.21	2.731 [.098]	2.865 [.091]
UNITEDPHOS	-0.039	0.097 [.756]	0.101 [.750]	0.22	3.004 [.083]	3.152 [.076]
USHABELTRO	0.105	0.677 [.410]	0.711 [.399]	-0.224	3.110 [.078]	3.263 [.071]
UTIBANK	-0.198	2.419 [.120]	2.538 [.111]	-0.286**	5.077 [.024]	5.327 [.021]
VDOCONINTL	0.260**	4.178 [.041]	4.383 [.036]	0.051	0.164 [.686]	0.172 [.679]
VIKASWSP	0.075	0.352 [.553]	0.369 [.543]	0.217	2.909 [.088]	3.052 [.081]
VOLTAS	-0.197	2.400 [.121]	2.518 [.113]	0.067	0.276 [.600]	0.289 [.591]
WARTDEISEL	-0.082	0.415 [.519]	0.436 [.509]	0.117	0.843 [.358]	0.885 [.347]

APPENDIX 6.4

Bootstrap Routine

The routine specified below was estimated using Resampling Stats software[68]. The programme reads the *S.S.M.E.* data in the file path c:\data. Column 1 in this file contained estimation period *S.S.M.E.s* whilst Column 2 contained event window *S.S.M.E.s*. The programme places Column 1 Data in a vector entitled "estim" and Column 2 Data in a vector entitled "event". These vectors are then combined in a single population, entitled "all". The repetitive routine then begins[69]. The population is shuffled, reordering the "all" data. The programme then picks 182 observations placing them in A$, and the remaining observations are allocated to Z$. The difference in means of the sub-samples is recorded and allocated in the vector "scrboard". After the repetition loop ends, the programme counts the number of instances where a mean difference of 0.164193 or higher was obtained. The p-value relating to the latter mean difference, is simply the number of instances where such mean difference (or higher) occurred, divided by 1000 (or 5000 when the routine is repeated 5000 times). Therefore, if we note 40 instances with such a mean difference (or higher), this would imply that there is a 4% chance that this mean difference occurs by pure coincidence. The p-value would therefore be 0.04. In such a case, the hypothesis of equal means of the original samples (i.e. estimation and event *S.S.M.E.s*), may be rejected at the customary 95% level of confidence.

```
READ file "C:\DATA" estim event
CONCAT estim event all
REPEAT 1000
  SHUFFLE all all
  TAKE all 1,182 A$
  TAKE all 183,364 Z$
  MEAN A$ mA$
  MEAN Z$ mZ$
  SUBTRACT mA$ mZ$ diff$
  SCORE diff$ scrboard
END
COUNT scrboard >=.164193 more
DIVIDE more 1000 prob
PRINT more prob
HISTOGRAM scrboard
```

[68] Information about this software is found on the internet web page http://www.resample.com/content/about.shtml (accessed 1st March 2004). The routine presented here is a modified version of another routine which is found on the same website.

[69] The routine in this programme covers 1000 re-sampling processes, due to software restrictions. Yet the actual programme was run for 5 successive times, resulting in 5000 different re-sampling processes. The results were then aggregated.

APPENDIX 6.5

Random Sub-Sampling for checking the consistency of the Cumulative Abnormal Returns Pattern.

Individual stocks were randomly assigned to one of the five sub-samples shown below. The computer generated a random number for each stock, by means of a spreadsheet. The stocks were then ordered starting from the smallest random number to the largest one. The first 36 stocks were assigned to Sub-Sample 1, the second and third 36 stocks were assigned to Sub-Sample 2 and Sub-Sample 3 respectively, and the next 37 stocks and the remaining ones were assigned to Sub-Sample 4 and Sub-Sample 5 respectively. For each sub-sample, the abnormal returns were averaged across stocks, and then summed across trading days. The cumulative abnormal return plot for each of the sub-samples is shown in Figure 6.5.

SUB-SAMPLE 1 (36 Stocks)

Amarajabat, Arvindmill, Bataindia, Bauschlomb, Bomdyeing, Bongairefn, Cmc, Coatviyela, Corpbank, Dabur, Esselpack, Germanrem, Gujratgas, Hdfcbank, Herohonda, Indrayon, Ioc, Jct, Kronecomm, Mahaintl, Max, Mcdowell, P&G, Pennaralum, Pfizer, Punjabtrac, Raincalcin, Ramanewspr, Raymond, Samtel, Silverline, Tatachem, Tatapower, Tatavashis, Telco, Tvselec

SUB-SAMPLE 2 (36 Stocks)

Adaniexpo, Aptech, Bajajauto, Bankpunjab, Bel, Bilt, Bindalagro, Birlaeric, Castrol, Ceat, Cochinrefn, Dcmdaewoo, Emerck, Essarship, Himachlfut, Hindevelop, Hindlever, Hindpetro, Indiacem, Insilco, Ipcalab, Lichsgfin, Lml, Mtnl, Nelco, Niit, Nocil, Padminpoly, Raslamipak, Relcapital, Reliance, Rhonepouln, Sbin, Suppetro, Tatafin, Tatatea

SUB-SAMPLE 3 (36 Stocks)

Apollohosp, Apollotyre, Bankbaroda, Bankindia, Bpcl, Bpl, Bses, Cadbury, Crompgreav, Dclpoly, Glaxo, Gujsidhcem, Hindzinc, Hocl, Idbi, Indal, Indhotel, Infotecent, Iti, Itil, Jindvijstl, Kesoramind, Mastplus91, Nepcmicon, Nilkamplst, Orientbank, Pentfrprod, Psidatasys, Rolta, Saloraintl, Shyamtele, Smithklpha, Spic, Spicelec, Sunpharma, Thomascook

SUB-SAMPLE 4 (37 Stocks)

Abb, Andhrapet, Ashokley, Britannia, Dlfcement, Drreddy, Escorts, Gnfc, Godrejsop, Grasim, Hindlevchm, Hindmotor, Hoteleela, Indogulf, Jpind, L&T, Leadedsys, Mastershar, Mastgain92, Moserbaer, Mrf, Nagarfert, Nestle, Novartis, Sail, Sanghipoly, Softsolint, Sqrdsfware, Srf, Sterlite, Surajdiamn, Tataelxsi, Unitedphos, Ushabeltro, Vdoconintl, Vikaswsp, Voltas

SUB-SAMPLE 5 (37 Stocks)

Bharatforg, Bhel, Carrierair, Centurytex, Colgate, Crestcomm, Digitaleqp, Finpipe, Fujitsicim, Gramophone, Gujambcem, Hcl-Hp, HindalcO, Icici, Icicibank, Ingerrand, Ipcl, Itc, Kecintl, Kopran, Krebsbio, Lakme, Laneseda, M&M, Madrasrefn, Mircelectr, Nirma, Parkedavis, Peerleship, Philips, Reckcolman, Shasunchem, Smitklbech, Spicfine, Tisco, Utibank, Wartdeisel

CHAPTER 7:

A MORE DETAILED INVESTIGATION OF VOLATILITY CHANGES FOLLOWING AUCTION SUSPENSION

7.1 Introduction

The evidence on changes in volatility following the suspension which was gleaned in the previous chapter did not yield clear inferences in any particular direction. The two different tests which were undertaken were both highly significant, but yielding contrasting indications. This chapter thus investigates the impact of the call auction suspension on NSE volatility in further detail, and thus it may be considered as an extension of the previous empirical investigation.

In the previous chapter, intra-day volatility was measured as the difference between the highest and lowest trading price of the day, scaled down by the opening price. Intra-day volatility decreased following the suspension, and the change was significant at the 99% level of confidence. Overnight volatility was assessed in terms of the Overnight Return Reversals, and reversals were more prominent following the auction suspension where the difference was significant at the 99% level of confidence. Thus, the first test indicated lower volatility following suspension, whilst the second one pointed at higher volatility following the suspension of the call auction.

This Chapter employs more rigorous measures of volatility. The main aim of this analysis is to model volatility around the auction suspension, with the intention of assessing whether the suspension resulted in overall higher or lower volatility. Various tests are thus applied, ranging from GARCH models to the scrutiny of return distributions and price movements during the day. Tests are conducted on monthly and daily data as well as observations sampled at higher frequencies.

The use of data sets sampled at different frequencies and the application of alternative tests to investigate the issue from multiple points of view is one of the inherent strengths of the analysis. In particular, the study investigates the impact of the call auction suspension on longer term inter-day volatility. This notion was sidelined in the previous chapter, on the grounds that market microstructure changes may only affect stock prices in the short-term, whereas over longer periods it is expected that prices become more influenced by the fundamental value of the firm. As outlined in the previous chapter, the analysis of the call auction suspension on NSE enables a relatively clear comparison in between systems.

The main objective of this analysis is to assess the volatility impact of the suspension of call auctions at the NSE, in terms of inter-day and intra-day volatility. If the auctions improved the price discovery process, one would expect to observe increased volatility following suspension – confirming the empirical results of Comerton-Forde (1999) who concluded that an exchange which commences the trading day with a call auction, rather than with continuous trading, may curtail volatility at the initial phases of the trading sessions. If on the other hand the call auctions did not contribute towards price formation, one may expect no material changes in volatility – or even a reduction in volatility following suspension. This would corroborate findings by Angel and Wu (2001) and Pouget (2004 b) who compared auctions to alternative settings, in terms of handling order imbalances and controlling deviations from equilibrium, respectively. Given that the evidence on call auctions and short-term volatility obtained so far was mixed, and that the link between market microstructure and longer-term volatility may be weak, it is difficult to infer *a priori* which of the above outcomes is more likely to be witnessed.

One major factor which poses challenges to the investigation of longer term volatility is the monthly seasonality pattern on NSE as discovered in Chapter 5. NSE volatility tends to increase during the months of March and April given that the accounting years of many companies end in March, coinciding with the end of the Indian fiscal year. Volatility tends to abate during August, perhaps due to a holiday effect. This pattern makes the original daily data biased in favour of the call auction suspension given that the higher volatility months coincide with the call auction period, whilst August coincides with the post-suspension period. In this way, the daily data set is adjusted for seasonality, given that the latter is unrelated to call auctions. The intra-day data set spans over a period of one and a half "normal volatility" months and therefore it should be less prone to seasonality.

With reference to the layout of this chapter, there is no designated literature survey, since the relevant literature regarding volatility concepts and GARCH Models was reviewed in Chapter 5, whilst possible relationships between auctions and volatility were discussed in Chapter 6. The reader is thus referred to the relevant Sections of these Chapters for a background of prior literature.

This analysis starts with a research background in terms of a description of the data set in Section 7.2. Following this, empirical models relating to volatility are estimated. Section 7.3 considers intra-day volatility, whilst Section 7.4 focuses on inter-day volatility. Results are jointly discussed in Section 7.5 where the empirical evidence is summarised and evaluated in the context of different indications at hand. Section 7.6 concludes.

7.2 Data and Notation

7.2.1 Intra-Day Data

The analysis uses intra-day observations of the NSE Nifty Index sampled at one-minute frequency. A description of the intra-day data sets and the sampling process was shown in Section 5.4.1. The data set includes fifteen trading days immediately preceding the auction suspension and a further fifteen days immediately following suspension. These trading days are labelled as B1...B15 (where B stands for "Before Suspension Period") and A1...A15 respectively (where A stands for "After Suspension Period"). Sampling at one minute frequency, yielded around 330 observations for each trading day.

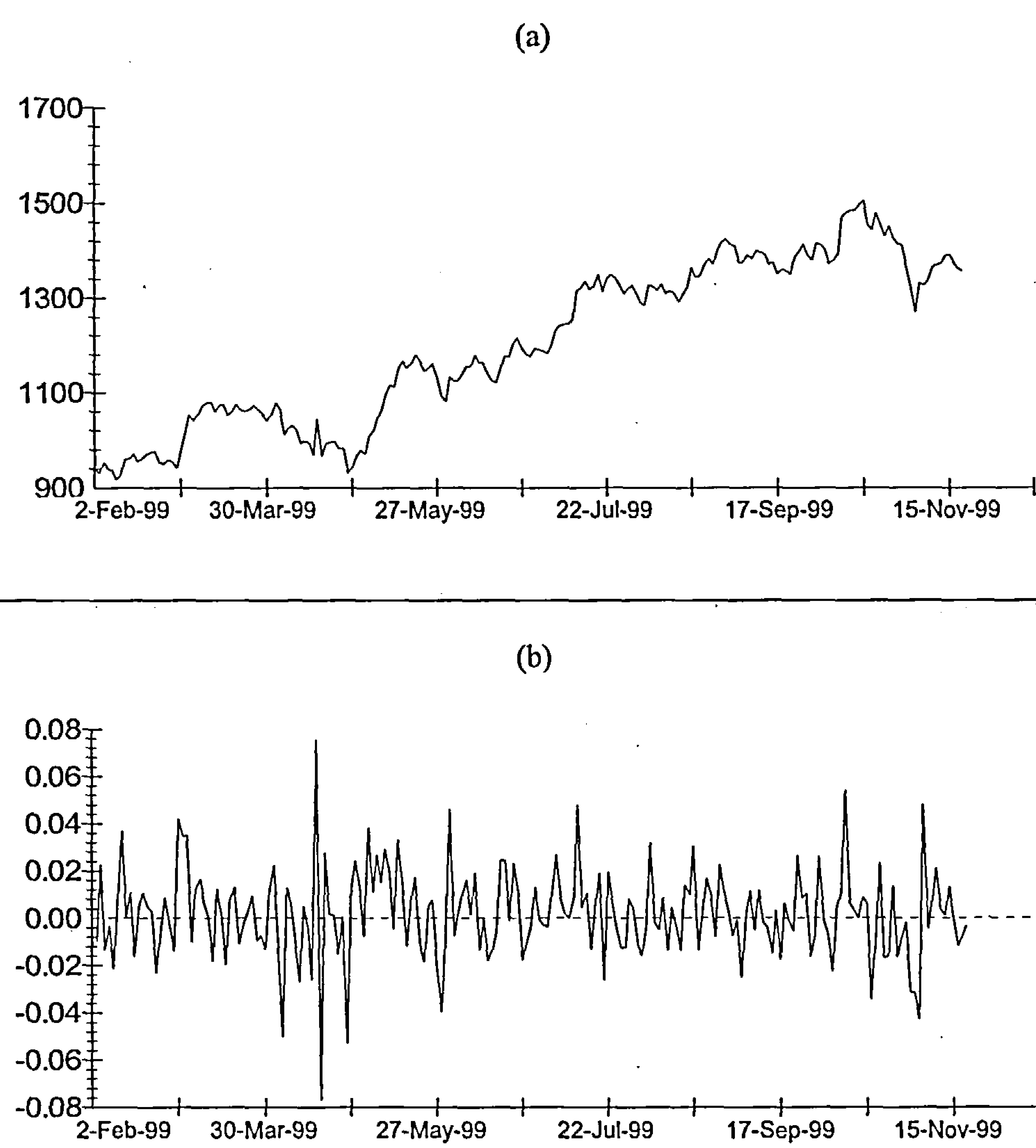
Descriptive statistics for the distributions of observations of each trading day are shown in Chapter 5 Table 5.1. In particular, the null hypothesis of a normal distribution was rejected for most data sets and the null hypothesis of a unit root for the intra-day log returns was rejected across all data sets.

7.2.2 Inter-Day Data

The daily data set shows the Nifty Closing observations from 1st February 1999 till 16th November 1999 and includes 204 observations. Whilst a longer series was available, the following models were estimated using only those days for which it could be established whether the trading sessions were commencing and closing through a call auction (therefore the remaining observations were not considered).

The plots of the Nifty (levels) series as well as log returns for the relative period are shown in Figure 7.1. The latter plot visually confirms that high volatility seems to cluster around specific periods as empirically found in Section 5.6. In particular volatility tends to be higher during the months of March and April and it tends to abate during the month of August.

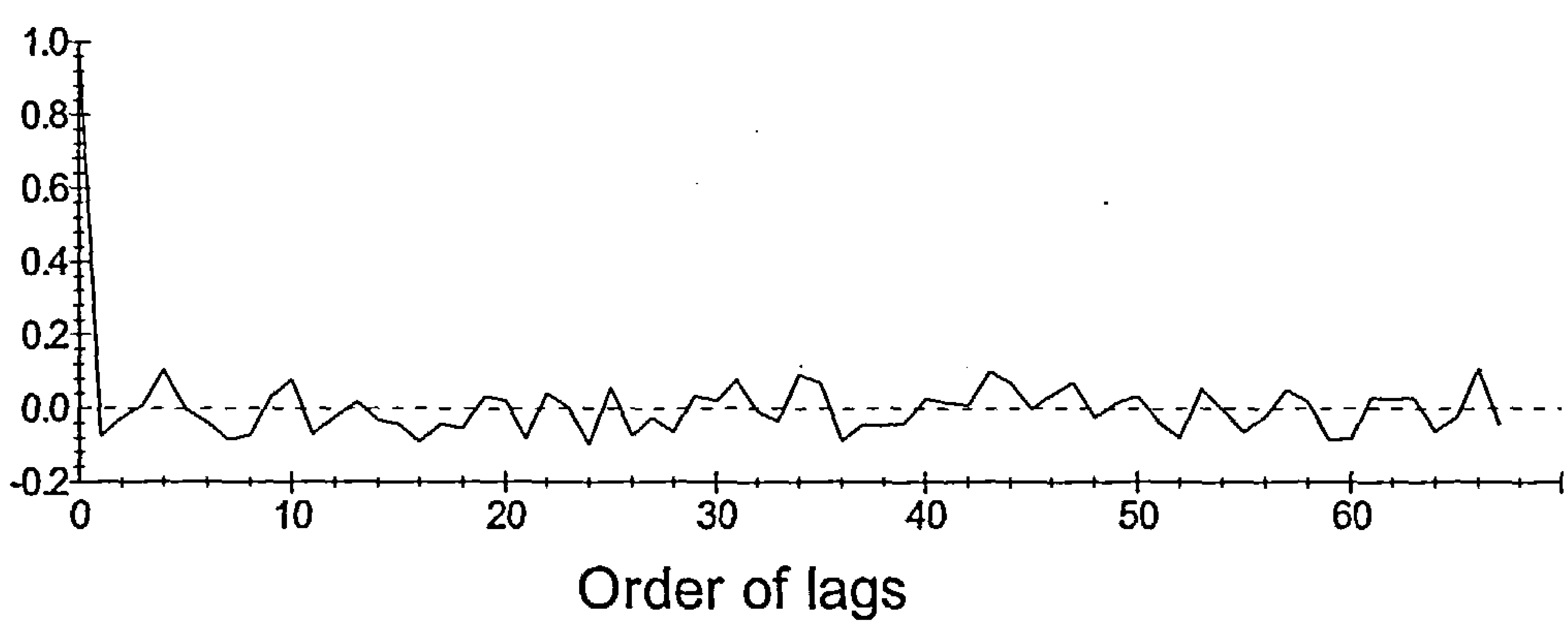
Figure 7.1: Time Series Plots for (a) Nifty Index and (b) Nifty Log Returns



The Nifty Log Return data set features an excess kurtosis of 2.35 and a skewness of -0.0087. A Jarque-Bera Test Statistic of 46.88 permits the rejection of the null hypothesis of normality at the 99% level of confidence when compared to the respective $\chi^2(2)$ critical value.

None of the autocorrelation coefficients of the log returns is significant. The autocorrelation function is shown in Figure 7.2. Augmented Dickey-Fuller test specifications with and without a trend yielded similar test-statistics as follows: -10.8 (Order 1), -5.5 (Order 5) and -4.4 (Order 10). Comparing the former statistics to the 95% critical values of -2.88 (test specification without a trend) and -3.43 (test specification with a trend) allows us to reject the Null Hypothesis of a Unit Root in log returns. GARCH models were thus estimated using Log Return Data.

Figure 7.2: Autocorrelation Function for Nifty Log Returns



7.3 Intra-Day Volatility

This section assesses whether the suspension of the call auctions led to any changes in intra-day volatility. For comparison purposes, it is essential to fit a uniform model across all intra-day data sets. The imposition of a uniform model on different data sets implies that a researcher cannot tailor-make models in order to maximise the overall statistical fit for each particular trading day. Therefore a thorough analysis of the data is essential in order to ensure that the functional form of the imposed model does not deviate largely from the main characteristics of the different data sets. This task is undertaken in the next sub-section. GARCH models are then fitted to the intra-day data sets in Section 7.3.2. Section 7.3.3 investigates the typical variations in volatility throughout the trading day and inquires whether the initial volatility constitutes price discovery or noise.

7.3.1 Analysing the Intra-Day Data Sets

The analysis started by aggregating the intra-day log returns at one-minute intervals, across the 15 trading days for the "Before Period" and the 15 trading days comprising the "After Period". The return plots shown in Figures 7.3 and 7.4 and are broadly in line with the empirical evidence cited in Section 5.2.1, regarding the higher volatility at the opening and at the closing of the trading day. Dummy variables were included in GARCH models to account for this factor, yet these estimations tended not to converge.

It would also have been desirable to model the actual opening and closing call auctions by a separate process, yet this was not possible given that in most cases, the auction time did not exceed five minutes, yielding five observations at one minute intervals (and in some cases even less).

Descriptive statistics and Augmented Dickey Fuller Tests for each of the trading days are shown in Chapter 5 Tables 5.1 and 5.2 respectively.

It is assumed that intra-day log returns follow an AR(ρ) process. AR(ρ) models with different values of ρ ranging from 0 to 5 were fitted to each intra-day data set, in order to infer the preferred model through the Akaike Information Criterion and the Schwarz Bayesian Criterion. Results shown in Table 7.1 indicate that both criteria select an AR(1) model for over half of the data sets and therefore this model is adopted as the standard return generating process.

Figure 7.3: Modulus of Returns – Call Auction Days

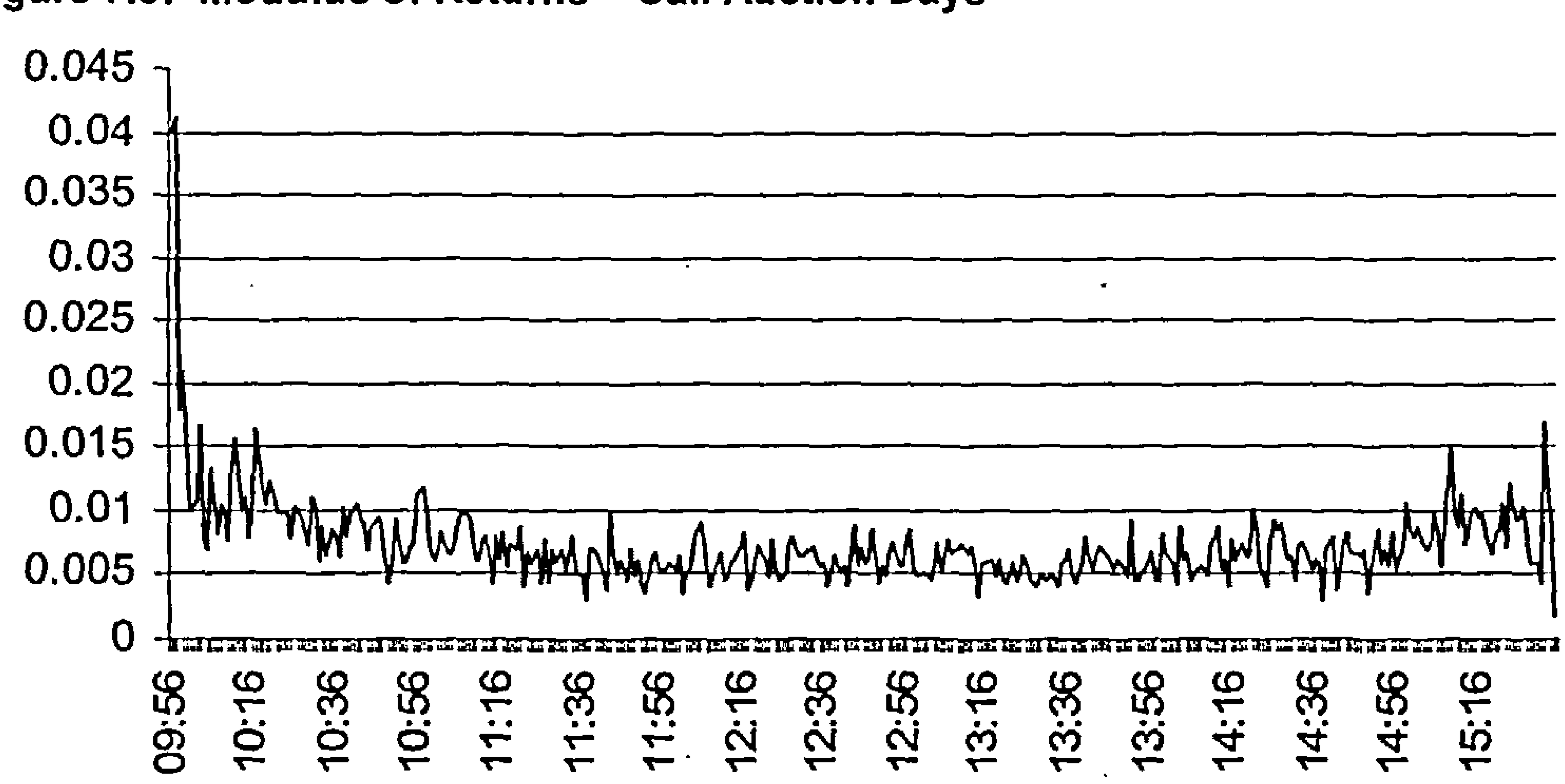
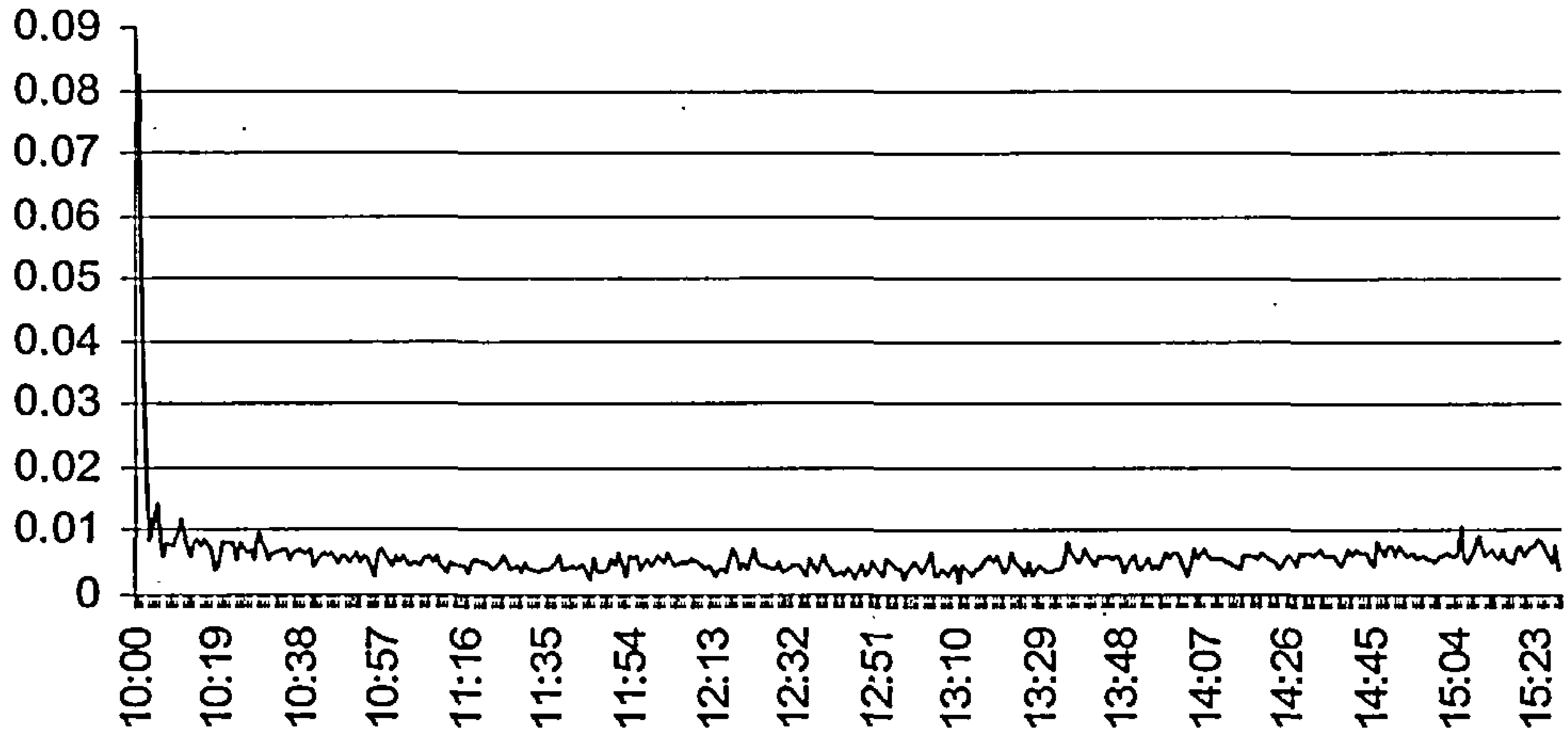


Figure 7.4: Modulus of Returns – Continuous Trading Days



Having selected an AR(1) specification for the intra-day log returns, we now test for the presence and nature of ARCH effects in the residuals of these processes. Table 7.2 summarises the results of LM heteroskedasticity tests as proposed by Engle (1982), together with the F-version of the test.[70] Actual test statistics are shown in Appendix 7.1. Order 1 and order 5 tests were conducted. The tests rejected the Null Hypothesis of no ARCH effects at the 95% level of confidence for around 50% of the data sets. This "low" rejection rate may be explained by various theoretical studies such as Drost and Nijman (1993). These authors specified that if daily returns follow a GARCH (1,1) process, intraday returns should follow a weak GARCH (1,1) process and the coefficients of α_I and β_I should tend to 1. The failure to reject the null hypothesis of no ARCH effects in about 50% of the cases, may also explain the non-convergence of some of the GARCH estimations – the actual return process might not have been following a GARCH pattern in these cases.

In order to choose the model which best describes the nature of the ARCH effects in the data, the level of asymmetry in the conditional volatility is now investigated. This should enable us to discriminate between linear and non-linear GARCH models. Engle and Ng (1993) outlined the following methodology for testing for asymmetric volatility:

$$\varepsilon_t^2 = \phi_0 + \phi_1 D_{t-1}^- + \xi_t \qquad (7.1)$$

Equation 7.1 regresses the squared error term from the AR(1) model over a constant, an error term and a dummy variable of the lagged error sign. When ε_{t-1} is negative D^-_{t-1} takes a value

[70] This test was described in Section 3.4.3.

of 1, whilst it takes a value of zero otherwise. Significance of D^{-}_{t-1} is an indication of asymmetric volatility. Test results are shown in Table 7.3 and indicate that D^{-}_{t-1} is only significant in case of four trading days, and therefore it is not advisable to use non-linear ARCH models, such as EGARCH or the GJR model for modelling intra-day data. This somewhat contradicts the earlier result discussed in Section 3.4 that high volatility tends to follow negative returns; yet the results in that particular instance were derived using observations at daily intervals. As outlined by Mutjaba Mian and Adam (2001) asymmetric volatility tends to decline in higher frequency data.

Table 7.1: Chosen AR(ρ) models for Intra-Day Log Returns (One-Minute Intervals)

Day	Maximum AIC	Chosen Model	Maximum SBC	Chosen Model
B01	2003	AR(4)	1997	AR(1)
B02	2030	AR(3)	2024	AR(2)
B03	2007	AR(1)	2003	AR(1)
B04	2018	AR(2)	2012	AR(2)
B05	2109	AR(2)	2103	AR(2)
B06	1911	AR(1)	1907	AR(1)
B07	1988	AR(1)	1985	AR(1)
B08	1878	AR(1)	1874	AR(1)
B09	1982	AR(2)	1976	AR(2)
B10	1973	AR(2)	1968	AR(2)
B11	2133	AR(2)	2127	AR(2)
B12	2120	AR(2)	2114	AR(2)
B13	2139	AR(1)	2135	AR(1)
B14	2076	AR(1)	2073	AR(1)
B15	2107	AR(5)	2096	AR(5)
A01	2022	AR(4)	2013	AR(3)
A02	2102	AR(1)	2098	AR(1)
A03	2062	AR(1)	2058	AR(1)
A04	2058	AR(2)	2053	AR(2)
A05	2079	AR(1)	2076	AR(1)
A06	1933	AR(2)	1927	AR(2)
A07	1991	AR(1)	1987	AR(1)
A08	2069	AR(1)	2065	AR(1)
A09	2129	AR(1)	2125	AR(1)
A10	2057	AR(1)	2053	AR(1)
A11	2000	AR(3)	1992	AR(3)
A12	2014	AR(2)	2009	AR(2)
A13	2101	AR(1)	2097	AR(1)
A14	2154	AR(1)	2150	AR(1)
A15	2152	AR(1)	2149	AR(1)

The table shows the following data for each daily log return price series: Columns 2 and 3 show the highest Akaike Information Criterion Value obtained when fitting AR(1) – AR(5) models and the chosen model following AIC. Columns 4 and 5 show the highest Schwarz Bayesian Criterion Value obtained when fitting AR(1) – AR(5) models and the chosen model following the SBC. Using both criteria, an AR(1) model is preferred for over half of the data sets.

Table 7.2: Rejection Rates of the Null Hypothesis of No ARCH Effects for different test specifications on One-Minute Frequency Data.

	Order 1	Order 5
LM Tests % of Days where the Null Hypothesis of No ARCH effects is rejected at the 95% confidence level	50%	57%
F-Tests % of Days where the Null Hypothesis of No ARCH effects is rejected at the 95% confidence level	50%	57%

The table shows the percentage occurrences where the Null Hypothesis of No ARCH effects in the error term was rejected, for different test specifications.

Table 7.3: Asymmetric Volatility Tests (D^{-}_{t-1}) for One-Minute Frequency Data

Day	Before Call Suspension			After Call Suspension		
	Coefficient	T-ratio	*Observations*	Coefficient	T-ratio	*Observations*
1	-0.8 $x10^{-7}$	(0.75)	*339*	2.7 $x10^{-7}$	(1.51)	*328*
2	-1.0 $x10^{-7}$	(0.74)	*338*	0.1 $x10^{-7}$	(0.33)	*328*
3	-0.4 $x10^{-7}$	(0.60)	*338*	0.1 $x10^{-7}$	(0.27)	*328*
4	0.5 $x10^{-7}$	(0.70)	*337*	-1.7 $x10^{-7}$ *	(1.92)	*328*
5	-0.1 $x10^{-7}$	(0.30)	*339*	0.5 $x10^{-7}$	(1.37)	*329*
6	-0.3 $x10^{-7}$	(0.20)	*336*	1.6 $x10^{-7}$	(0.65)	*328*
7	3.4 $x10^{-7}$ **	(2.30)	*339*	-0.7 $x10^{-7}$	(1.09)	*328*
8	-0.3 $x10^{-7}$	(0.18)	*337*	-0.7 $x10^{-7}$ *	(1.73)	*328*
9	-7.2 $x10^{-7}$	(0.90)	*338*	-0.1 $x10^{-7}$	(0.38)	*329*
10	1.0 $x10^{-7}$	(0.85)	*338*	0.5 $x10^{-7}$	(1.03)	*329*
11	0.3 $x10^{-7}$	(0.43)	*337*	1.1 $x10^{-7}$	(1.09)	*328*
12	-0.3 $x10^{-7}$	(0.65)	*337*	0.7 $x10^{-7}$	(1.18)	*328*
13	-0.1 $x10^{-7}$	(0.38)	*337*	0.1 $x10^{-7}$	(0.29)	*329*
14	-0.4 $x10^{-7}$	(0.51)	*336*	-0.3 $x10^{-7}$	(1.01)	*329*
15	-1.3 $x10^{-7}$ *	(1.67)	*340*	0.2 $x10^{-7}$	(0.53)	*328*

The table shows the coefficient of D^{-}_{t-1} which accounts for asymmetric volatility as per the methodology proposed by Engle and Ng (1993). T-ratios are shown next to the coefficients. Significance at the 95% and the 90% confidence levels is denoted by ** and * respectively. The number of observations available for regression estimation is shown in italics.

7.3.2 Intra-Day GARCH Processes

This section shows the estimation of the actual GARCH models and it investigates the differences between the "Before Period" and the "After Period". Since it is desirable to fit a uniform model to all data sets for comparison purposes, the chosen specification is GARCH (1,1). This follows the observation of Andersen and Bollerslev (1997) that this model usually provides an acceptable estimate. Therefore returns are modelled as an AR(1) process, whilst heteroskedasticity is modelled as shown in Equation 7.2 hereunder:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{7.2}$$

where h_t is the conditional variance which depends on past information, and ε_t^2 is the unexpected return observed during period t.

Two different GARCH models were attempted for each trading day: the first model assumed that the conditional distribution of the errors was normal whilst the second model assumed that it followed a student-t distribution. In the former case, three out of thirty estimations failed to converge, whilst in the latter case, ten estimations failed to converge.

A number of estimated models were omitted for any one of the following three reasons. Models were omitted when a Wald Test failed to reject the Null Hypothesis that $(\alpha + \beta)$ was equal to one. This violates the required stationarity condition of GARCH models and indicates a unit root in the return variance. Other models were omitted given that the estimated coefficient for the lagged conditional variance in the GARCH equation was negative and highly significant. Such a coefficient does not make sense as outlined by Engle (2001). The third criterion for model omission was negative R^2 statistics indicating very poor explanatory power. In these cases, the software did not provide an F-statistic for the models, probably due to the same reason.

The Akaike Information Criterion and the Schwarz Bayesian Criterion were used to select the preferred model for each trading day – whether to use the normal distribution model or the t-distribution one. In those cases where these criteria selected different models, the choice was done according to the Akaike Information Criterion. For those trading days where no choice of model was possible (due to estimation failures or omitted models), the only available model was retained. This process resulted in 23 estimations available for analysis; 13 for the "Before Period" and 10 for the "After Period" as shown in Tables 7.4 and 7.5.

The GARCH (1,1) model estimations presented in Tables 7.4 and 7.5 show that the AR(1) coefficient of the return equation is significant. According to Fama (1970) this indicates that the market is not even weak-form efficient since past returns may be used to (partly) predict current returns. Yet, we should also state that some degree of serial correlation may be expected in high-frequency data, where returns tend to be affected by market factors such as the splitting of large orders into smaller ones. Despite the high significance of the AR(1) coefficient, the regressions have modest explanatory power as inferred from the R^2 statistic. As regards the conditional variance equation, most of the *alphas* and *betas* are significant, and Wald tests reject the null hypothesis that $\alpha_1 + \beta_1 = 0$ for all the estimations. We thus infer that lagged errors and shocks have a significant effect on conditional volatility.

Table 7.4: GARCH Models for one minute-frequency data - "Before Period"

Day	AR Intercept $\hat{\varphi}$	AR Lag $\hat{\rho}$	R^2	Coeff: $\hat{\omega}$	Coeff: $\hat{\alpha}_1$	Coeff: $\hat{\beta}_1$	Wald
B 1	-0.000008	0.4095 ***	0.1613	0.0000003	0.1226	0.1992 *	14.8
t	(0.25)	(7.75)		(0.07)	(1.25)	(1.84)	{65.9}
B 2	0.000018	0.2757 ***	0.1102	0.0000000	0.0185	0.9506 ***	63509.7
n	(0.58)	(5.47)		(0.00)	(1.34)	(63.33)	{62.3}
B 3	-0.000027	0.4386 ***	0.1916	0.0000000	0.0457	0.8967 ***	10545.7
t	(0.80)	(8.90)		(0.00)	(1.31)	(26.17)	{38.0}
B 4	0.000022	0.3881 ***	0.1121	0.0000000	0.0346	0.8593 ***	6574.7
n	(0.67)	(7.65)		(0.01)	(1.51)	(34.82)	{92.4}
B 5	0.000026	0.2838 ***	0.0925	0.0000000	0.0626 **	0.8780 ***	9889.6
n	(1.04)	(5.45)		(0.00)	(2.36)	(32.67)	{38.8}
B 6	-0.000027	0.3747 ***	0.1680	0.0000000	0.1505 ***	0.7985 ***	3962.3
n	(0.70)	(6.56)		(0.01)	(2.71)	(17.25)	{7.4}
B 8	-0.000038	0.4000 ***	0.1129	0.0000000	0.0835 **	0.8655 ***	8665.2
n	(0.82)	(7.83)		(0.01)	(2.29)	(25.90)	{21.2}
B 9	0.000043	0.3750 ***	0.1789	0.0000000	0.2257 ***	0.6496 ***	1211.5
n	(1.59)	(7.11)		(0.01)	(3.37)	(12.06)	{17.4}
B 10	0.000021	0.3500 ***	0.1327	0.0000000	0.0939 **	0.8756 ***	7225.3
t	(0.65)	(6.67)		(0.00)	(2.21)	(24.75)	{4.5}
B 11	0.000010	0.3923 ***	0.1339	0.0000000	0.0344 *	0.9260 ***	28603.8
n	(0.44)	(7.74)		(0.00)	(1.70)	(44.94)	{48.3}
B 13	-0.000001	0.2195 ***	0.1927	0.0000000	0.0773 **	0.8578 ***	5168.3
t	(0.05)	(4.34)		(0.00)	(2.15)	(26.05)	{21.4}
B 14	-0.000009	0.3283 ***	0.0840	0.0000000	0.0664	0.8334 ***	1902.2
t	(0.38)	(6.24)		(0.01)	(1.37)	(20.17)	{17.8}
B 15	0.000028	0.4129 ***	0.2092	0.0000001	0.2977 ***	0.3661 ***	154.4
n	(1. 23)	(8.74)		(0.00)	(3.49)	(5.43)	{34.1}

The first column shows the trading day, whilst the letter underneath indicates whether the conditional distribution for the error terms was assumed to be normal (n) or student-t (t). Log returns were modelled as an AR(1) process, where φ refers to the intercept and ρ is the estimated coefficient of the lagged return. T-ratios are shown in brackets underneath the coefficients and significance at the 99%, 95% and 90% confidence levels is denoted by ***, ** and * respectively. R^2 shows the explanatory power of the regression. The coefficients of the GARCH process are ω (the intercept), α_1 (lagged error term) and β_1 (lagged conditional variance). The final column shows the results for the Wald Tests on the GARCH process. The null hypothesis of the first test is that $\alpha=0$ and $\beta=0$. The test is $\chi^2(2)$ distributed with a 95% critical value of 5.991. The result for the second Wald test is shown in braces underneath. The null hypothesis is that $\alpha_1+\beta_1=1$ and the test is $\chi^2(1)$ distributed with a 95% critical value of 3.841. When the null hypothesis was not rejected, the particular model was discarded and therefore it is not shown in the table. The observations available for each model estimation ranged from 336 to 340. (The actual number of observations in respect of each trading day is shown in Table 7.3).

Table 7.5: GARCH Models for one minute-frequency data - "After Period"

Day	AR Intercept $\hat{\varphi}$	AR Lag $\hat{p}$	R^2	Coeff: $\hat{\omega}$	Coeff: $\hat{\alpha}_1$	Coeff: $\hat{\beta}_1$	Wald
A 2	-0.000016	0.2634 ***	0.1563	0.0000000	0.0426 **	0.9358 ***	37260.4
n	(0.76)	(5.20)		(0.00)	(2.04)	(47.82)	16.0
A 3	-0.000018	0.3003 ***	0.0771	0.0000000	0.0420	0.9448 ***	39661.2
t	(0.79)	(5.59)		(0.00)	(1.61)	(40.67)	4.8
A 4	0.000034	0.3343 ***	0.5643	0.0000000	0.0475 **	0.8857 ***	12464.2
n	(1.56)	(7.63)		(0.00)	(2.18)	(38.45)	63.9
A 7	0.000019	0.3382 ***	0.0728	0.0000000	0.0618	0.8567 ***	4496.6
t	(0.65)	(6.45)		(0.00)	(1.11)	(15.96)	33.4
A 9	0.000032	0.2957 ***	0.1558	0.0000000	0.0448	0.8647 ***	5377.8
t	(1.53)	(5.52)		(0.00)	(0.88)	(16.89)	53.0
A 11	-0.000040	0.3704 ***	0.1453	0.0000000	0.0227	0.9370 ***	15808.4
t	(1.46)	(7.41)		(0.00)	(1.18)	(49.33)	26.5
A 12	-0.000007	0.3961 ***	0.1859	0.0000000	0.0732 *	0.7430 ***	1625.9
n	(0.26)	(7.50)		(0.01)	(1.84)	(17.67)	81.7
A 13	-0.000008	0.3721 ***	0.1356	0.0000000	0.0372	0.9017 ***	14297.6
n	(0.34)	(7.14)		(0.00)	(0.95)	(23.56)	57.9
A 14	-0.000015	0.2332 ***	0.0203	0.0000000	0.1548 **	0.5373 ***	156.2
t	(0.82)	(3.90)		(0.01)	(2.17)	(7.71)	28.7
A 15	-0.000007	0.3129 ***	0.0845	0.0000000	0.0579	0.7502 ***	688.5
t	(0.39)	(5.75)		(0.01)	(0.96)	(12.67)	36.2

The first column shows the trading day, whilst the letter underneath indicates whether the conditional distribution for the error terms was assumed to be normal (n) or student-t (t). Log returns were modelled as an AR(1) process, where φ refers to the intercept and p is the estimated coefficient of the lagged return. T-ratios are shown in brackets underneath the coefficients and significance at the 99%, 95% and 90% confidence levels is denoted by ***, ** and * respectively. R^2 shows the explanatory power of the regression. The coefficients of the GARCH process are ω (the intercept), α_1 (lagged error term) and β_1 (lagged conditional variance). The final column shows the results for the Wald Tests on the GARCH process. The null hypothesis of the first test is that $\alpha=0$ and $\beta=0$. The test is $\chi^2(2)$ distributed with a 95% critical value of 5.991. The result for the second Wald test is shown in braces underneath. The null hypothesis is that $\alpha_1+\beta_1=1$ and the test is $\chi^2(1)$ distributed with a 95% critical value of 3.841. When the null hypothesis was not rejected, the particular model was discarded and therefore it is not shown in the table. The observations available for each model estimation were 328 or 329. (The actual number of observations in respect of each trading day is shown in Table 7.3).

According to Franses and Van Dijk (2000), the unconditional mean of ε_t^2 or the unconditional variance of ε_t is equal to:

$$\sigma^2 = \frac{\omega}{1-\alpha-\beta} \tag{7.3}$$

Volatility is expected to converge to this value over the long-term. α_1 and β_1 are the ARMA components of the conditional variance i.e. the unexpected lagged return and the lagged conditional variance. One may interpret these as temporary deviations around the unconditional variance which depend on past information. Most of these coefficients, especially those relating to β_1, are significant and we may conclude that there is a substantial degree of persistence in the NSE Nifty index, when sampled at one-minute frequency.

T-tests were conducted on the coefficients obtained for the returns and conditional variance equations in order to infer any significant differences in between the "Before Period" and the "After Period". The results are shown in Table 7.6. The reduction in α_1 was significant at the 90% level of confidence, when considering the critical value for a one-tailed test. The reduction in α_1 did not lead to any significant difference in the combined GARCH coefficients as shown by the t-test on $\alpha_1 + \beta_1$. Yet, the results indicate an overall highly significant drop in the unconditional variance of ε_t as shown in the last column. This is in line with the evidence of a reduction in intra-day volatility (Section 6.4.1), where this was modelled by the Intra-Day Scaled Price Difference for individual stocks. Despite this, one should also note that the latter result from the previous Chapter was also coupled by a significant increase in Overnight Return Reversals and thus the relationship between the call auctions and the overall volatility is still unclear.

Table 7.6: T-Tests for Return and GARCH Model Coefficients (estimated through one-minute frequency data)

	$\hat{\varphi}$	$\hat{\rho}$	$\hat{\omega}$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\alpha}_1+\hat{\beta}_1$	$\hat{\omega}/(1-\hat{\alpha}_1-\hat{\beta}_1)$
Mean (Before)	0.0000044	0.358	0.000000047	0.101	0.766	0.867	0.00000036
Mean (After)	-0.000003	0.322	0.000000017	0.058	0.836	0.894	0.00000018
Variance (Before)	0.0000000	0.004	0.000000000	0.007	0.052	0.033	0.00000
Variance (After)	0.0000000	0.003	0.000000000	0.001	0.016	0.009	0.00000
Pooled Variance	0.0000000	0.003	0.000000000	0.004	0.037	0.023	0.00000
t-Statistic	0.686	1.455	1.242	1.534 *	-0.865	-0.429	2.833 ***
95% Critical Value (one-tail)	1.721	1.721	1.721	1.721	1.721	1.721	1.721
95% Critical Value (two-tail)	2.080	2.080	2.080	2.080	2.080	2.080	2.080

The table shows the results for t-tests to infer any significant differences in the coefficients between the "Before Period" and "After Period". Statistics were based on 13 observations for the "Before Period" and 10 observations for the "After Period". Significance at the 99%, 95% and 90% confidence levels is denoted by ***, ** and * respectively.

While the reduction in α is only significant at the 90% level of confidence when considering a one-tailed test, and the increase in β is insignificant, there is an overall highly significant drop in the unconditional variance of ε_t as measured by the expression $[\omega / (1-\alpha-\beta)]$.

The reported t-tests assumed equal variances between the "Before Period" and the "After Period" in respect of each coefficient. T-tests assuming unequal variances were also conducted. The latter tests led to the same inferences, except that the reduction in ω becomes significant at the 90% level of confidence, when considering a one-tailed test.

7.3.3 Intra-Day Return Distributions

The second test on changes in intra-day volatility following the call auction suspension considers the intra-day return distributions. Particular emphasis is laid on the opening observations, given that any expected effects of opening auctions should be noted at the initial observations of the particular day (and similarly, most effects of closing call auctions can only be assessed in view of the initial observations of the following day).

Figures 7.3 and 7.4 confirm that volatility tends to reach its peak during the initial half hour of trading, and then rises again towards the end of the trading day – although it does not typically reach the opening levels. This section investigates the differences between the opening, middle-of the-day, and closing volatility and aims to highlight any changes in these factors following the call auction suspension. A test is also undertaken in order to assess whether the initial volatility constitutes price discovery or noise.

A note on the approach of analysing the return distributions is warranted prior to presenting the empirical results. Different methodological approaches were attempted to model changes in volatility throughout the trading day. The inclusion of dummy variables did not result in successful outcomes. Therefore, this rather "rudimentary" approach was adopted, involving the analysis of the basic characteristics of the returns at each of the particular trading day sections. This approach is not necessarily an inferior one. According to Dacorogna, *et. al.* (2001; pp. 44) in case of high-frequency data, realized volatility may prove to be a superior measure than modelled volatility such as the estimates obtained through GARCH estimations.

The first 40 (one-minute) observations for each trading day were considered in compiling statistics for the opening period. Similarly, the last 40 observations were used for compiling statistics relating to the closing. The rest of the observations were labelled as "middle of the day".

The summary statistics are shown in Table 7.7. When considering the average statistics for the 30-day period, it is evident that volatility is highest at the opening, whilst closing volatility is higher than that of the middle of the day. This may be inferred both through the standard deviations of returns, as well as the maximum and the mean of squared returns. In addition, the largest return during the day tends to occur at the opening as shown in Figures 7.3 and 7.4. It is also evident that the opening return distributions are the ones which deviate most from the normal distribution, in terms of skewness and excess kurtosis. As may be expected, the skewness is closer to zero for the middle of the day distributions and this may be attributed to the fact that these distributions include roughly five times as many observations as the other ones. A higher amount of observations makes it less likely that the distribution skews to any particular direction.

Table 7.7: Summary Statistics For Return Distributions Sampled at One-Minute Intervals

		LOG RETURNS			SQUARED LOG RETURNS			
		St.Dev	Skew.	K-3	Mean	St.Dev	Max	Min
Op.	Avg : 30 Days	0.0012	0.835	6.710	0.00000193	0.0000068	0.0000403	0
Mid.	Avg : 30 Days	0.0005	-0.048	1.312	0.00000027	0.0000005	0.0000041	0
Cl.	Avg : 30 Days	0.0007	0.155	0.428	0.00000055	0.0000009	0.0000041	0
Op.	Avg: Before	0.0012	0.339	4.313	0.00000164	0.0000047	0.0000278	0
Op.	Avg: After	0.0012	1.330	9.106	0.00000222	0.0000088	0.0000528	0
Mid.	Avg: Before	0.0006	-0.131	1.740	0.00000034	0.0000006	0.0000054	0
Mid.	Avg: After	0.0004	0.035	0.884	0.00000020	0.0000003	0.0000028	0
Cl.	Avg: Before	0.0008	0.156	0.692	0.00000079	0.0000014	0.0000062	0
Cl.	Avg: After	0.0005	0.153	0.165	0.00000031	0.0000004	0.0000020	0

The Columns indicate the following: (1) Period of the Day (Opening / Middle / Closing); (2) Average for the particular period (Whole Sample / Before Period / After Period); (3) Standard Deviation of Returns; (4) Skewness of Returns; (5) Excess Kurtosis of Returns; (6) Mean of Squared Returns; (7) Standard Deviation of Squared Returns; (8) Maximum Squared Return; and (9) Minimum Squared Return. The opening and closing distributions consisted of 40 observations. The observations for the middle-of-the-day ranged from 248 to 260.

In testing for the differences in volatility during the Opening, Middle of the Day and the Closing, two volatility proxies were used. These were the Mean Squared Returns and the Return Standard Deviations for the particular period of the day – these were first estimated for each section of the thirty trading days, and then an average was computed for the Opening, Middle Of the Day and the Closing.

The differences between the Mean Squared Returns at the Opening, Middle-of-the-Day and Closing were tested through two-tailed Paired Sample t-tests. Results shown in Table 7.8 Panel A reject the hypotheses of no difference between the mean squared returns across the trading day. Similarly, two-tailed Paired Sample t-tests were conducted on the return standard deviations during different periods of the trading day. Table 7.8 Panel B shows that the results are qualitatively analogous. Overall, this confirms the pattern of a reverse-J-shape in volatility (and returns).

Table 7.8: T-tests on Differences in Volatility During the Trading Day.

PANEL A: Two-Tailed Paired Sample T-Tests Tests on Mean Squared Returns

Null Hypothesis	Outcome - Confidence Level	T-Statistic	Two-Tailed Critical Value
No Diff. Between Open. & Mid.	Rejected - 99%	3.60	2.76 (99%)
No Diff. Between Open. & Clos.	Rejected - 99%	2.83	2.76 (99%)
No Diff. Between Mid. & Clos.	Rejected - 95%	2.22	2.05 (95%)

PANEL B: Two-Tailed Paired Sample T-Tests Tests on Return Std. Deviations

Null Hypothesis	Outcome - Confidence Level	T-Statistic	Critical Value
No Diff. Between Open. & Mid.	Rejected - 99%	6.21	2.76 (99%)
No Diff. Between Open. & Clos.	Rejected - 99%	4.45	2.76 (99%)
No Diff. Between Mid. & Clos.	Rejected - 99%	3.62	2.76 (99%)

The t-tests are based on the statistics of the 30 sampled trading days; and thus 30 observations were available for each of the opening, closing and middle-of-the-day periods. All t-tests reject the null hypothesis of no difference between the respective volatility proxies during the different periods of the day.

The Mean Squared Returns and the Return Standard Deviations Statistics were estimated through one-minute frequency data.

The differences between the "Before Period" and the "After Period" across these different sections of the trading day are now analysed. The statistics for the Opening Distributions as shown in Table 7.7 indicate that following the suspension of the call auction, the initial volatility increased (in terms of the mean of squared returns, standard deviation of squared returns, and maximum squared returns). This is in contrast to the Middle-of-the-Day and the Closing distributions which overall indicate lower volatility.

One may also note differences in terms of deviations of the return distributions from normality – although this does not necessarily serve as an indication with respect to volatility. The opening return distributions for the "After Period" deviate more from normality in terms of skewness and excess kurtosis. Conversely, the Middle-of-the-Day and the Closing distributions indicate convergence towards normality following the auction suspension.

As regards the kurtosis for the whole 30 days, the opening returns tend to be the most "peak shaped". This also indicates that whilst the opening is typically more volatile, it is also characterised by a number of returns which are very close to zero. The plots of the log returns across trading days confirm that the opening is characterised by a large return which takes place within the first minutes, which is then followed by smaller returns. This pattern suggests that prices seem to fluctuate, initially in response to overnight news and subsequently depending on temporary liquidity features such as remaining order imbalances. This point is investigated further underneath. Provided that the large return is not subsequently reversed, this suggests that most of the initial price discovery occurs within the interval of one or two minutes. Yet, if the large return is subsequently reversed, this implies that the initial volatility might comprise noise.

Prior to presenting the empirical results, one should note that a limitation of this methodology is that the underlying news pattern (which is not observed) may in fact mean that in some Reversal instances, the initial volatility may still have been justified, and similarly a Reinforcement does not necessarily imply that the opening return was justified. Yet, it may be expected that over a 30 trading-day sample this methodology yields reasonable indications. In addition no material differences in news arrivals are expected to prevail between the "Before" and "After" periods.

A further limitation of the methodology is that it may be biased in favour of reinforcements. As outlined by Madhavan, Richardson and Roomans (1997), reinforcements may be more likely than reversals given that larger orders are typically executed in smaller components and due to other market factors such as price continuity rules.[71]

Table 7.9 shows the statistics relating to the Reversal-Reinforcement Test. The opening returns were defined as the percentage (nominal) return from the opening till 10:15. [72] The return plots confirmed that in most cases, the large return at the opening occurred during the initial 15 minutes, and it is therefore captured in this period. The subsequent returns were then measured as the return from 10:15 till 12:30 and the return from 10:15 till the closing. When the direction of the opening return did not subsequently change, it suggests that the opening return was justified and it is labelled as a Reinforcement. Those cases where the return changed sign are labelled as Reversals, and indicate that the opening return may have been noise.

[71] The typical bid-ask bounce may potentially lead to an opposite effect (a relatively high amount of reversals) when analysing individual stock or derivative data at short enough intervals, as discussed by Buckle, Gwilym, Thomas and Woodhams (1998). Whilst the concept of bid-ask spreads is less relevant in those settings where transactions are not intermediated via market-makers (such as NSE), such effect might still transpire given that trades may usually be classified as "buyer-initiated" or "seller-initiated", depending on whom of the parties has a higher incentive or urgency to transact.

[72] In case of the post-suspension period, this constitutes the return during the first 15minutes of trading, whilst it represents a longer trading time in case of the pre-suspension period, owing to the additional call auction trading.

The results shown in Table 7.9 indicate that Reversals are more prominent than Reinforcements, and overall they do not provide evidence that the initial opening returns are justified. This suggests that the opening stages are prone to unjustified price fluctuations, and it explains why market designers have typically implemented features to assist price discovery during this period (such as pre-opening periods and call auctions).

Table 7.9: Intra-Day Return Patterns

Day	Op - 10:15	10:15-12:30	10:15-Cl	RF / REV - 12:30	RF / REV - Cl.
B 1	0.56%	1.44%	0.16%	RF	RF
B 2	1.30%	0.61%	0.45%	RF	RF
B 3	0.85%	-1.01%	-1.90%	REV	REV
B 4	-0.66%	1.07%	1.09%	REV	REV
B 5	-0.13%	0.62%	0.89%	REV	REV
B 6	0.61%	-1.99%	-2.72%	REV	REV
B 7	-0.49%	1.53%	-3.41%	REV	RF
B 8	0.09%	-2.50%	-1.01%	REV	REV
B 9	3.53%	-0.09%	1.14%	REV	RF
B 10	-1.01%	1.47%	0.29%	REV	REV
B 11	-0.28%	-0.90%	0.41%	RF	REV
B 12	0.73%	-0.35%	0.26%	REV	RF
B 13	1.90%	-0.40%	-0.26%	REV	REV
B 14	0.68%	0.08%	-0.51%	RF	REV
B 15	-1.42%	1.85%	3.26%	REV	REV
A 1	-0.05%	0.01%	-1.45%	REV	RF
A 2	1.00%	-0.21%	-1.11%	REV	REV
A 3	-0.08%	-1.40%	-1.67%	RF	RF
A 4	-3.02%	0.47%	2.10%	REV	REV
A 5	0.48%	0.08%	-1.44%	RF	REV
A 6	-0.24%	-0.41%	2.80%	RF	REV
A 7	0.95%	1.09%	1.48%	RF	RF
A 8	0.27%	0.08%	-0.47%	RF	REV
A 9	0.87%	0.63%	1.44%	RF	RF
A 10	0.62%	0.44%	0.59%	RF	RF
A 11	0.41%	-1.79%	-2.49%	REV	REV
A 12	-0.48%	-0.64%	-0.58%	RF	RF
A 13	0.53%	0.42%	-0.74%	RF	REV
A 14	0.48%	-0.73%	-0.51%	REV	REV
A 15	-0.19%	-0.56%	-0.31%	RF	RF
TOTAL DAYS:				**REV: 16 RF: 14**	**REV: 18 RF: 12**
BEFORE SUSPENSION PERIOD:				**REV: 11 RF: 4**	**REV: 10 RF: 5**
AFTER SUSPENSION PERIOD:				**REV: 5 RF: 10**	**REV: 8 RF: 7**

The returns columns show the % changes in nominal prices from the opening to 10:15, from 10:15 till 12:30, and from 10:15 till the end of the day. When the direction of the opening return is the same as that of the subsequent return, the "pattern" is classified as a Reinforcement (RF). When the opening return changes direction during the rest of the day, the "pattern" is classified as a Reversal (RV).

Yet, the statistics reported in Table 7.9 do not provide overall evidence that the auction setup on NSE was assisting in price discovery. When considering the differences between the call auction regime and the trading days without auctions, the reversals are more prominent in the call auction period. Therefore, the higher initial volatility following the auction suspension (Table 7.9) should be interpreted with caution, since it might be the case that although there were higher price movements, the latter were in fact justified.

The Reinforcement / Reversal ratios provide further evidence that the expected theoretical benefits of auctions were not being realised on NSE, and they support the evidence presented in the previous chapter that the suspension of the call auctions led to higher efficiency and lower intra-day volatility. The latter evidence was gathered over a 120-trading day period, and therefore provides confidence that the former intra-day results are not a "peculiar observation".

Thus, although at face value one may argue that the call auctions were contributing towards reduced opening volatility, doubts are cast about this statement when considering whether the initial price movements were reversed later on during the day or otherwise. Yet, one should also be cautious before attributing such price movements to the call auctions themselves. While it might be the case that the call auctions were not contributing to price discovery, it might still be unreasonable to state that the auctions were pushing prices in the "wrong" direction. This goes against the fundamental features of auction principles and it might be more sensible to attribute such inconsistencies to traders' actions. In particular, it might be the case that some traders were submitting "mispriced" orders to misguide other traders, and cancelling such orders before they are executed, as suggested for instance by Biais, Hillion and Spatt (1999) in respect of the (former) Paris Bourse. Such participants then trade profitably as the price movements are reversed.

If traders indeed use opening call auctions to misguide other participants, then one natural question would be why they do not use the closing call auctions in a similar manner. Firstly, there is no evidence that mispriced orders are not submitted at the closing call auction as well. Indeed, prior literature suggests that there are participants who may be interested in manipulating closing prices. The latter may include brokers who might try to influence closing prices in order to give the impression of smart order execution capability to their clients (Hillion and Suominen; 2004). Despite this, there are also reasons why traders may prefer to submit mispriced orders earlier during the day, rather than at the closing auctions.

Comerton-Forde and Rydge (2006 a) showed that manipulation is less costly in a situation when there are relatively few orders on the book. Thus, one may infer that opening auctions could have been more suited for manipulation since these were less active than the closing ones. Another reason why traders might have preferred to use opening auctions for manipulation is that they might not have been interested in misguiding participants during the overnight period, given that no organised trading takes place overnight, and therefore it might be difficult to take advantage of the information asymmetry. A related aspect is that inferring the real value of a stock during the overnight period may be more difficult due to the absence of trade reporting. In addition, if the mispriced order is executed in the closing auction, traders may have to withstand undesired overnight positions. This would present the risk that adverse overnight news may swamp any expected profits from anticipated price reversals. These risks might become even more pronounced when holding exposures during the weekend closure, as per the empirical evidence of Brailsford (1995) in respect of Australian equity market volatility. The submission of mispriced orders towards the closing may also be hindered by increased trading costs towards the end of the day. One possible reason for such increased costs may be that fund managers postpone their trades towards the closing, and this creates increased demand for immediacy (Cushing and Madhavan; 2001).

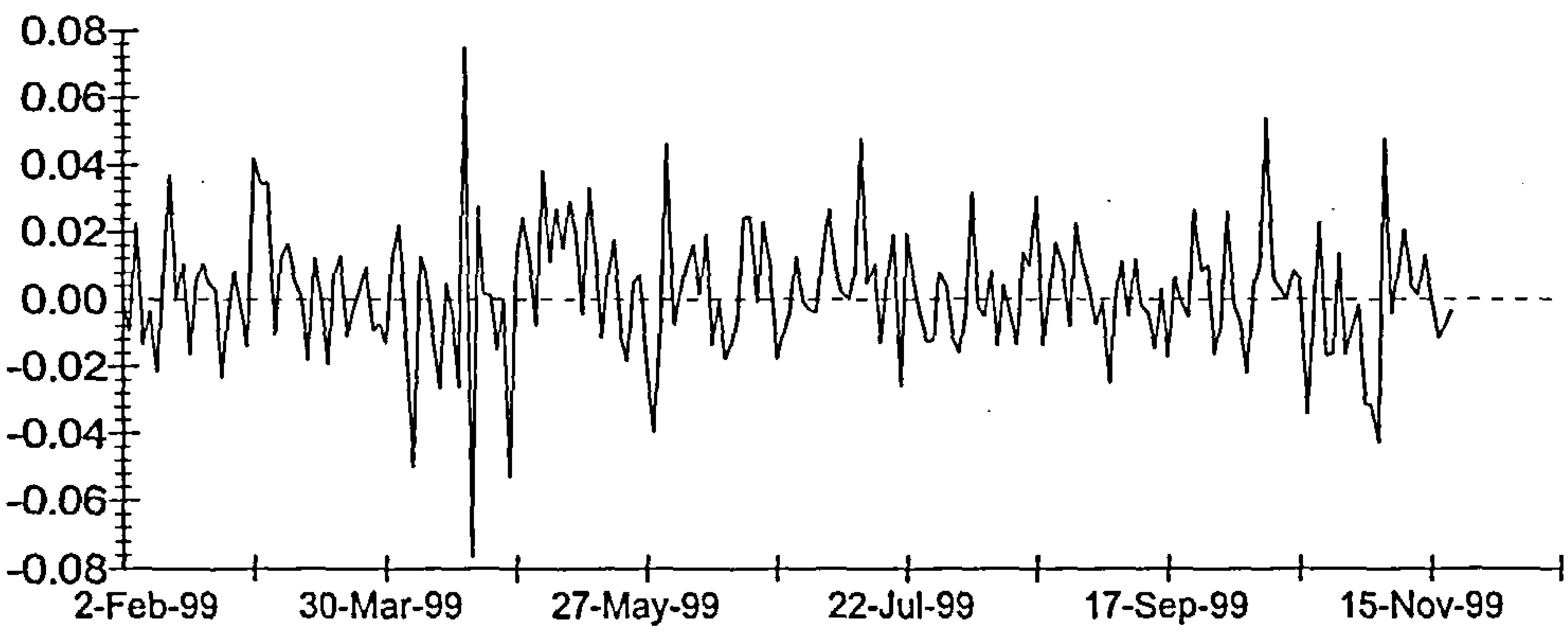
The statistics for the middle-of-the-day and the closing hint at a lower volatility following the call auction suspension. This is in line with the decline in the unconditional variance following suspension (Section 7.3.2).

7.4 Inter-Day Volatility

Given that the daily data feature seasonality effects (Section 5.6) it is biased towards indicating higher volatility during the call auction period, since the higher volatility months (March and April) coincide with the call auction system, whilst the lower volatility month (August) forms part of the post-suspension period. This monthly seasonality was detected over a five year period, and thus it is not related to the call auctions themselves.

To exclude these seasonal effects, the data were adjusted as follows. Log returns during the months of March and April as compared to the rest-of-the-year are in the ratio of 1.0043 : 1 (Chapter 5 Table 8). Conversely, the ratio of the rest-of-year log returns to August log returns is 1 : 0.9974. As a simple adjustment for this seasonality, the March and April log returns were divided by 1.0043, whilst the August log returns were divided by 0.9974.[73] The plot of the Nifty Log Returns adjusted for seasonality is shown in Figure 7.5.

Figure 7.5: Nifty Log Returns adjusted for Monthly Seasonality



As a preliminary test, the Modulus of Seasonally-Adjusted Nifty Log Returns series was regressed as follows:

$$Y = \pi + \beta D_A + \xi \tag{7.4}$$

where Y is the Seasonally-Adjusted Log Modulus Return series, π and β are estimated coefficients and ε is an error term. D_A is a dummy variable which takes the value of 1 during the call auction period (1st February 1999 till 8th June 1999) and zero otherwise. The results shown in Table 7.10 Panel A indicate that volatility was higher during the call auction period, and the dummy variable is significant at the 95% confidence level. Yet a closer look at Figure 7.5 shows "spikes" in the Seasonally-Adjusted Log Return series that coincide with the month of April. Considering the possibility that these large returns were due to new information, rather than the call auction itself, the four largest observations during the month of April were eliminated. These observations ranked as the first, second, fourth and fifth largest in the whole data set. When the regression shown in Equation 7.4 was re-estimated in the absence of these "outliers", D_A was not even significant at the 90% confidence level, as shown in Table 7.10 Panel B.

[73] The tests undertaken on the adjusted log returns data were also replicated on the unadjusted log returns. No material differences were noted in the empirical results.

Table 7.10: Regressing Seasonally-Adjusted Daily Log Returns Modulus on A Call Auction Dummy

PANEL A: Data comprised the whole sample of Seasonally-Adjusted Log Returns

Intercept (π)	Auction Dummy (D_A)	Explanatory Statistics	
0.0122 ***	0.0040 **	R-Squared	0.0238
(10.24)	(2.21)	{R-bar-Squared	0.0189}

PANEL B: Data did not include the 4 largest April observations

Intercept (π)	Auction Dummy (D_A)	Explanatory Statistics	
0.0122 ***	0.0017	R-Squared	0.0066
(12.20)	(1.14)	{R-bar-Squared	0.0015}

The table shows the results obtained when regressing the Seasonally-Adjusted Nifty Log Return Modulus series, over an intercept, and a dummy variable which took the value of 1 during the call auction period and zero otherwise. Panel A shows the first estimation using all 203 sampled observations, whilst Panel B shows the second estimation, where the four largest April observations were eliminated (199 observations). Regression coefficients are shown on top, whilst t-ratios are reported in brackets underneath. Explanatory statistics are shown in the third column. Significance is denoted by ***, **, and * for the 99%, 95%, and 90% confidence level respectively.

Thus, this preliminary test yields an indication against the call auction setup, albeit not clearly significant. We now progress with the estimation of GARCH models using the seasonally-adjusted daily data.

7.4.1 Preliminaries for fitting GARCH models

In order to infer the model which best captures the return generating process, six AR(ρ) models were estimated with ρ ranging from 0 to 5. Both the Schwarz Bayesian Criterion and the Akaike Information Criterion selected an AR(0) process.

Having selected an AR(0) specification for the daily log returns, we now test for the presence and nature of ARCH effects in the residuals of this process through LM heteroskedasticity tests as proposed by Engle (1982).[74] Order 1 and order 5 tests yielded LM statistics of 20.1 and 21.5 respectively. The tests permit the rejection of the Null Hypothesis of no ARCH

[74] This test was described in Section 3.4.3.

effects at the 99% level of confidence, when comparing the LM statistics to the Chi-Squared statistics at the respective degrees of freedom.

The test of Engle and Ng (1993) was used to infer whether a GARCH process which accounts for asymmetric volatility is required (Equation 7.1). In this case, the coefficient of the lagged dummy D^{-}_{t-1} was 0.00008 with a standard error of 0.0001 and this is indicates that any asymmetric responses are insignificant. Thus it is unnecessary to use models which account for asymmetric volatility.

In attempting to fit GARCH models to the data, the majority of estimations failed to converge. Therefore, Absolute Value GARCH (AGARCH) models were estimated as alternatives. An AGARCH model assumes that the conditional volatility is affected by the current and past conditional volatility, and by the current and past absolute value of the shocks. Thus the conditional volatility equation of an AGARCH model is specified as follows:

$$\sqrt{h_t} = \omega + \alpha_1 |\varepsilon_{t-1}| + \beta_1 \sqrt{h_{t-1}} \tag{7.5}$$

where h_t is the conditional variance which depends on past information, and ε_t^2 is the unexpected return observed during period t. Empirical results are shown in the next Section.

7.4.2 The Impact of Call Auction Suspension on Inter-Day Volatility

Two different approaches were selected for inferring the impact of the call auction suspension on volatility. The first approach involved further use of the dummy variable D_A which takes the value of 1 during the call auction period, and the value of zero for the rest of the observations. This dummy variable was included in the conditional variance equation of the AGARCH model. Estimation results are shown in Table 7.11. The second approach involved the estimation of two separate AGARCH models for the "Before Period" and the "After Period". The results are shown in Table 7.12 Panels A and B.

The results of the dummy variable approach, suffer from low explanatory power in terms of R^2. The intercept of the log return process is significant at the 90% level. As regards the conditional variance equation, the Wald-Tests do not permit the rejection that the coefficients are equal to zero. The dummy variable D_A is positive, indicating a higher conditional variance in the call auction regime. The dummy variable is *nearly* significant at the 90% level of confidence, both through a Wald-Test and a comparison of the coefficient with the standard error.

Table 7.11: AGARCH Model for daily Nifty log returns with Auction Dummy

Log Return AR(0) Process:

Intercept	R {bar} ^{2}
0.0020 *	-0.0001
(1.61)	{-0.0151}

Conditional Variance Equation:

Coeff: ω	Coeff: α_1	Coeff: β_1	Coeff: D_A
0.0184 ***	0.1887 **	-0.2747	0.0055
(2.79)	(2.35)	(0.66)	(1.57)

Wald Test Statistic for the Null Hypothesis that $\alpha_1 + \beta_1 + D_A = 0$:
0.0386 as compared to a Chi Squared (1) Critical Value of 2.71at the 90% level of confidence.

Wald Test Statistic for the Null Hypothesis that $\alpha_1 + \beta_1 = 0$:
0.04349 as compared to a Chi Squared (1) Critical Value of 2.71 at the 90% level of confidence.

Wald Test Statistic for the Null Hypothesis that $D_A = 0$:
2.4978 as compared to a Chi Squared (1) Critical Value of 2.71 at the 90% level of confidence.

The conditional volatility equation includes a dummy variable D_A, which takes the value of 1 for the call auction regime, and a value of zero when no call auctions were held. 204 observations were available for model estimation. T-ratios are shown in brackets underneath the respective coefficients. Significance at the 99%, 95% and 90% levels of confidence is denoted by ***, ** and * respectively. The Adjusted R^2 is shown in braces underneath the R^2 statistic.

The low significance of the dummy variable is not surprising. The previous evidence presented in Chapter 6 regarding the impact of the auction suspension on volatility was mixed. In addition, it may also be justified to expect call auctions to impact more heavily on intra-day volatility rather than inter-day volatility, given that the long-term value of stocks is more dependent on the fundamental value of the firms, rather than on the setup in which they trade.

These considerations, coupled with the low explanatory power of the mean equation limit the potential for meaningful inferences. The results of this test are thus consistent with the previous ones, in that we only obtain weak evidence against the call auction setup.

The results obtained from the second approach of estimating a separate AGARCH model for both regimes are presented in Table 7.12, Panels A and B. Overall these results do not contradict the above arguments. Again, the AR(0) process is characterised by negative R^2 statistics which limit the overall significance of any inferences. Yet, the conditional heteroskedasticity equation is characterised by non-negligible changes across the regimes.

Table 7.12: AGARCH Models for daily Nifty log returns

Panel A: Before Call Auction Suspension

Log Return AR(0) Process:

Intercept	R {bar} ^{2}
0.0043 *	-0.0070
(1.81)	{-0.0301}

Conditional Variance Equation:

Coeff: ω	Coeff: α_1	Coeff: β_1
0.0172 ***	0.2983 **	-0.0347
(2.97)	(2.08)	(0.13)

Wald Test Statistic for the Null Hypothesis that $\alpha_1 + \beta_1 = 0$:
0.8745 as compared to a Chi Squared (1) Critical Value of 2.71 at the 90% level of confidence.

Panel B: After Call Auction Suspension

Log Return AR(0) Process:

Intercept	R {bar} ^{2}
0.0013	-0.0001
(0.90)	{-0.0181}

Conditional Variance Equation:

Coeff: ω	Coeff: α_1	Coeff: β_1
0.0239 ***	0.1613	-0.6100 ***
(5.31)	(1.49)	(2.64)

Wald Test Statistic for the Null Hypothesis that $\alpha_1 + \beta_1 = 0$:
2.5161 as compared to a Chi Squared (1) Critical Value of 2.71 at the 90% level of confidence.

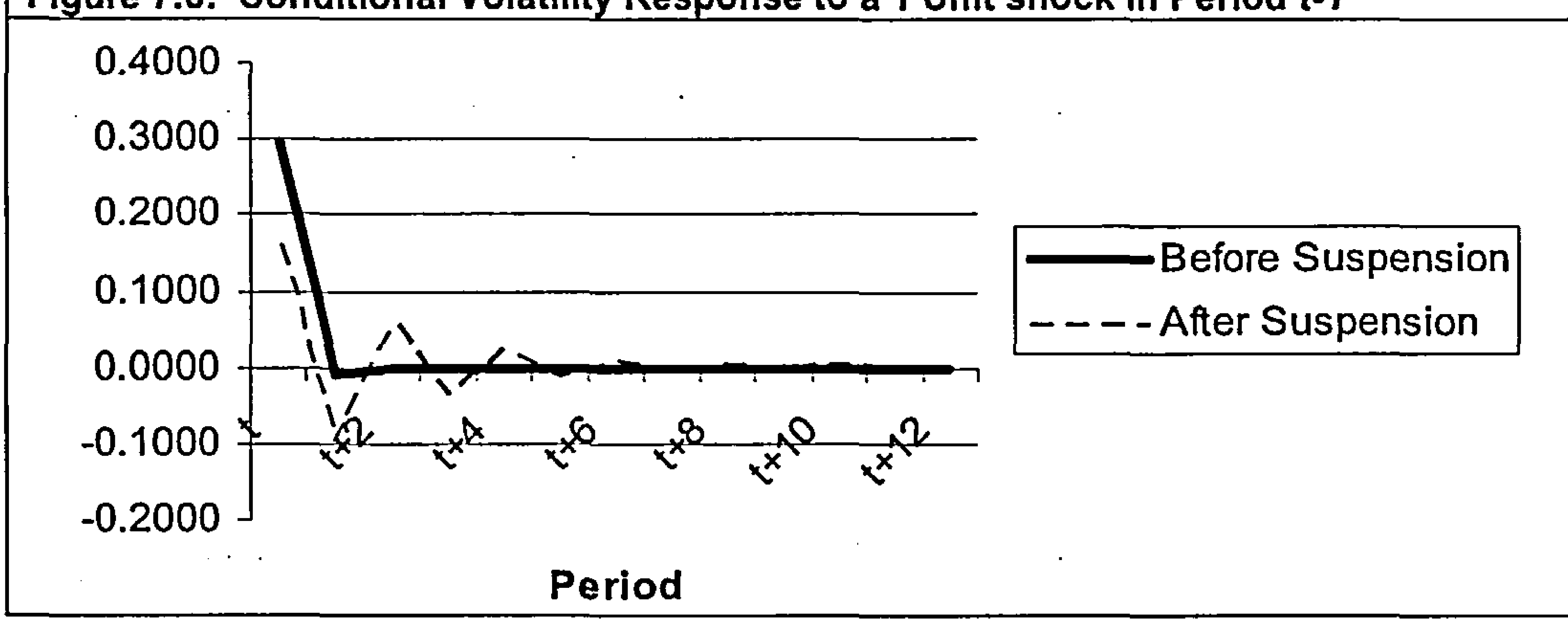
90 observations were available for estimating the Before Suspension model, whilst 114 observations were available for the After Suspension period. T-ratios are shown in brackets underneath the respective coefficients. Significance at the 99%, 95% and 90% level of confidence is denoted by ***, ** and * respectively. The Adjusted R^2 is shown in braces underneath the R^2 statistic.

The initial constant in the conditional volatility equation ω, is highly significant. The increase in the intercept may indicate a higher overall conditional volatility following the call auction suspension.

As regards the other components of the conditional standard deviation equation, the coefficient of α_1 is only significant in the "Before Period", whilst the coefficient of β_1 is only significant in the "After Period". The problem with the latter coefficient is that a negative and significant lagged conditional volatility does not make sense outlined by Engle (2001). Alternative GARCH models were thus estimated, however the significantly negative lagged volatility component still prevailed.[75]

Relying on the above results we may state that in the call auction period, shocks had a higher impact on the conditional standard deviation in those periods immediately following the shock, whilst following call auction suspension, the response of the conditional standard deviation to lagged shocks decreased. Conversely, β_1 which is an AR effect of the conditional standard deviation is more significant in the "After Period". Thus, whilst the initial response to a shock is lower following auction suspension, the response "trails on" to a higher extent in the "After Period". These effects are shown in Figure 7.6 which traces the response of the conditional standard deviation to a 1 unit shock in period *t-1*.

Figure 7.6: Conditional Volatility Response to a 1 Unit shock in Period *t-1*



This leads on to the question as to which period is characterised by the overall higher volatility. Unlike most of the other tests, these models tend to favour the call auction period. Firstly, the intercept of the conditional volatility equation ω is lower in the call auction period, indicating a lower overall conditional volatility in the latter period. In addition, the volatility of the "Before Period" behaves more in line as expected in an efficient market, in that new shocks have an immediate impact on volatility – indicating that new information is priced in immediately, and the impact of news becomes less prominent in later periods.

Overall, the GARCH tests seem inconclusive, given that whilst the first test points that the call auction period was characterised by a higher conditional volatility, the second test shows that

[75] The specifications AR(1)-AGARCH (1,1), AR(0)-EGARCH (1,1), and AR(1)-EGARCH(1,1) still resulted in a significantly negative lagged volatility for the "After Period". When an AR(0)-AGARCH (2,1) model was specified, this resulted in a significantly negative lagged volatility for the "Before Period", rather than the "After Period".

the conditional volatility seems be more in line with an efficient market in the call auction period. However, this inference as regards higher efficiency following the call auction suspension conflicts with the evidence presented in Chapter 6, where the Relative Return Dispersion decreased significantly following the auction suspension.

7.5 Discussion

This analysis considered changes in inter-day and intra-day volatility around the suspension of opening and closing call auctions on NSE. The original data set sampled at daily frequency was adjusted to take account of monthly seasonality of volatility as discovered in Chapter 5.

The tests on intra-day data (Section 7.3) point at a significant drop in the response of the conditional variance to lagged shocks as well as a highly significant drop in the unconditional variance following the call auction suspension. In addition the post-suspension period is characterised by lower volatility in the middle-of-the-day and the closing return distributions. The opening volatility was higher in the post-suspension period, yet tests on the reinforcements and reversals of price movements indicate that this higher volatility might have been justified. The reinforcement-reversal tests cast doubts as to whether any expected benefits of call auctions were materialising on NSE, since the call auction period is characterised by a relatively high amount of reversals of the opening returns. The tests on intra-day data thus seem to confirm the previous chapter's overall evidence against the efficacy of call auctions – particularly the shortcomings of the opening one.

Tests on the seasonally-adjusted daily data (Section 7.4) revealed that the log returns were higher in absolute value during the call auction period; yet we cannot be sure whether this is a remnant of the seasonal volatility pattern on NSE – indeed the difference becomes insignificant when the four largest observations for the month of April are eliminated. Modelling volatility through an AGARCH process indicates higher conditional volatility in the call auction period through a positive dummy variable, although the latter is not significant at the 90% confidence level. Estimating separate AGARCH models for the "Before Period" and the "After Period" yields potentially contrasting results, in that the conditional volatility seems higher following call auction suspension, and the impact of shocks (news) is more in line with an efficient market in the "Before Period".

In trying to fit the puzzle together it might be sensible to give more weighting to the tests conducted on intra-day data on various grounds. Firstly, any benefits of call auctions might be expected to materialise in the shorter-term, whereas longer-term volatility should be more influenced by news rather than the market microstructure setup. Secondly, given that the intra-day data set spans over a period of around one and a half months it should be less prone to monthly seasonality whereas traces of seasonality might still be present in the seasonally-adjusted data set. Thirdly, the majority of the tests carried out on daily data do not have sufficient statistical significance and some of the coefficients do not make economic sense. Finally, the daily data tests yield potentially conflicting results.

Volatility seems higher during the call auction period, although we cannot rule out that this is due to the news release patterns on NSE. The tests conducted on intra-day data seem to favour the suspension of the call auction. Perhaps the strongest result in this respect is the ratio of Return Reversals: Reinforcements. Reversals of opening returns tend to be more prominent in the call auction period and this raises the question of whether the expected benefits of opening call auctions were materialising on NSE.

Overall, this (contrasting) evidence might not serve as a case for the universal suspension of call auctions – indeed this is by no means being hinted. Yet this evidence is useful from the point of view of market designers who should avoid thinking of call auctions as a *carte blanche* for lower market volatility and higher efficiency. Thought has to be laid on the actual design of auctions and to the possibilities that these might not attract sufficient trading activity as outlined by Schwartz (2000), and that they may be used to misguide traders' expectations as suggested by Biais, Hillion and Spatt (1999).

One aspect of auction design which might be particularly challenging is transparency. Low levels of transparency, might imply that if the market clearing price deviates considerably from the true value of the asset, then the correctly-priced orders might remain undisplayed to the market at large. Conversely, increased transparency may facilitate collusion in between traders (since it might make it easier to infer the strategies of other participants) and it increases the cost of the "free option" problem related to limit orders (Madhavan, Porter and Weaver; 2005). Increased transparency may also translate in lower efficiency if it makes it easier for market participants to disseminate imprecise information which overshadows real news (Brandouy, Barneto and Leger; 2003). Indeed, according to Vickery (1961) the optimal auction structure when only one unit of the asset is available, involves *sealed* bids i.e. minimal transparency. Yet, this might not be applicable to those cases when multiple units are being traded (Morgan; 2001). Klemperer (2000) suggested the use of an Anglo-Dutch auction where the initial phase of the auction is transparent, yet the final phase involves sealed bids. Despite this, the relevance of such an auction to securities markets is questionable: splitting the auction in two phases, would require the submission of at least two prices – this involves considerable human effort, and it is therefore likely to raise transaction costs prohibitively, say when a broker is required to trade fifty different stocks. In addition, an auction where the final phase is not transparent may reduce the traders' confidence in the procedure.

Designers should also consider whether auctions might make sense in the particular circumstances; for example, the use of auctions to misguide participants may be more prevalent in India where markets were traditionally characterised by insider dealing and market manipulation as discussed by Shah and Sivakumar (2000) and Agarwal and Singh (undated).

7.6 Conclusion

This analysis employed a battery of tests on intra-day and inter-day data to assess the impact of the suspension of call auctions on NSE volatility. The empirical evidence is somewhat mixed – yet we may claim that we did not obtain any clear evidence that call auctions on NSE were resulting in significant benefits. This broadly confirms the conclusions obtained in the previous Chapter – in particular the likelihood that the opening call auction was less effective than one may expect. One possibility is that the auction setup on NSE was not suitable for the particular market characteristics as outlined in the previous section.

These results add further evidence to that of the existing literature, and they also indicate other areas of required research. The latter include more theoretical and empirical modelling regarding call auction suitability within different market setups. The interaction of call auctions (or their absence) with other market microstructure features may yield invaluable insights as to why the expected theoretical benefits of call auctions may not always materialise. A crude answer as suggested in this analysis might be that auctions are at times incorrectly structured. Yet, the question still remains as to the factors which should be considered in assessing the desirability of auctions for particular markets, and how to design the "optimal" call auction for a given trading setup.

APPENDIX 7.1

Testing for ARCH Effects in Intra-Day Data sampled at one-minute intervals

Day	Order (1) Tests		Order (5) Tests	
	LM Test	F-Test	LM Test	F-Test
B01	1.73	1.72	1.17	0.23
B02	66.57 **	82.16 **	10.89	2.20
B03	0.30	0.30	27.36 **	5.83 **
B04	1.50	1.49	16.78 **	3.46 **
B05	5.44 **	5.48 **	23.53 **	4.95 **
B06	1.67	1.66	15.42 **	3.16 **
B07	60.52 **	73.02 **	66.04 **	16.06 **
B08	5.01 **	5.04 **	12.08 **	2.45 **
B09	15.22 **	15.8 **	72.67 **	18.13 **
B10	6.90 **	6.98 **	5.06	1.01
B11	13.28 **	13.71 **	4.82	0.96
B12	0.57	0.57	7.54	1.51
B13	4.52 **	4.54 **	30.18 **	6.49 **
B14	0.00	0.00	1.93	0.38
B15	84.68 **	111.77 **	74.83 **	18.8 **
A01	104.91 **	152.84 **	35.01 **	7.67 **
A02	0.30	0.30	16.52 **	3.41 **
A03	8.87 **	9.03 **	15.53 **	3.19 **
A04	56.37 **	67.45 **	82.12 **	21.44 **
A05	11.13 **	11.42 **	13.28 **	2.71 **
A06	1.84	1.84	15.53 **	3.19 **
A07	0.13	0.13	6.98	1.40
A08	0.03	0.03	9.77	1.97
A09	0.17	0.17	5.85	1.17
A10	10.42 **	10.67 **	13.72 **	2.8 **
A11	1.05	1.05	3.45	0.68
A12	1.77	1.76	5.14	1.02
A13	1.24	1.24	3.36	0.66
A14	12.31 **	12.67 **	19.28 **	4.01 **
A15	0.01	0.01	5.98	1.19

The table shows the results for various ARCH tests specifications on the 30 intra-day data sets. The time-series for each trading consisted of a number of observations ranging from 328 to 340. (The actual number of observations in respect of each trading day is shown in Table 7.3). Order (1) and Order (5) tests were conducted; both through LM methodology as outlined by Engle (1982), as well as the F-version of the tests. A rejection of the Null Hypothesis of No Arch Effects at the 95% level of confidence is denoted by **. The χ^2 Critical Values (95%) are 3.84 [for the Order (1) test] and 11.07 [Order (5)]. The F-Critical Values (95%) are: 3.89 [for the Order (1) test] and 2.27 [Order (5)].

CHAPTER 8: CONCLUSION

This dissertation presents a series of original findings from a diversity of empirical techniques applied to data which were sampled at different frequencies. This concluding chapter highlights the motivation behind the research undertaken and summarises the main findings. It also discusses the contribution of this research to the existing literature and to finance practitioners. The findings are evaluated in the context of the limitations of the methodologies employed, and directions for future research are pointed out.

8.1 Motivation Behind the Undertaken Research

The main topics tackled in the previous empirical chapters were selected on a number of grounds. Firstly, traditional financial theory has difficulty explaining asset price movements. The relatively new discipline of market microstructure offers an opportunity to account for part of the unexplained price fluctuations especially when these seem unrelated to fundamentals. Thus the empirical investigations in this dissertation offer the potential to *further understand the price formation process.*

Another motivation behind the research was the increased importance being devoted to emerging markets on part of financial practitioners. Countries such as India and China are taking up a larger share of the global production of goods and services, yet it does not seem that the emergence of these economies has been accompanied by an equally prominent surge in academic interest. Researching the market microstructure setup of emerging markets presents a significant potential to extend existing literature, since the findings obtained when studying the former markets may differ from those prevailing in established ones, given the differing characteristics of emerging markets in terms of liquidity and efficiency. It is hoped that these empirical studies will contribute towards bridging this gap.

There are additional factors which explain the choice of the actual market microstructure issues tackled in this dissertation. The issue of non-synchronous trading is important because it impacts on various inferences which may be obtained when analysing stock market data; for instance the degree of market efficiency and whether there is any potential for abnormal profits emanating from delayed adjustments in the expectations of market participants. The finance discipline stands to gain from a deeper understanding of non-synchronous trading effects and further empirical evidence gleaned through various methodologies.

The second investigation centred on volatility. Volatility is directly related to returns and to risks, and one important research question is whether markets are excessively volatile. The detection and the controlling of unjustified volatility is a central objective of market microstructure researchers and practitioners. The issue of whether volatility is justified or excessive is central to the market microstructure field, since it translates into whether asset prices exclusively reflect the underlying information, or whether they are additionally subject to other extraneous factors.

The last two empirical investigations focused on the impacts of the suspension of the opening and closing call auctions on NSE. This issue falls within one of the most important branches of market microstructure i.e. the design of trading protocols and the evaluation of their effectiveness. The efficacy of call auctions as compared to other trading setups attracted much attention in previous research. NSE proved an ideal empirical setting for the call auction investigation, given that the suspension occurred in the absence of any other changes in trading protocols. In addition, a further gap in the prior empirical literature on call auctions was that the latter tended to focus on the stock markets of the major industrial countries. Being an emerging market exchange, NSE features a significant proportion of less liquid securities, and this enabled the investigation of the differences in the impacts concerning more and less liquid securities on the market.

Finally, the first two empirical investigations on non-synchronous trading and volatility are relevant in analysing subsequent issues. For instance some of the price movements noticed when modelling volatility on NSE, may be attributable to non-synchronous trading effects. Similarly, background knowledge of volatility seasonality is necessary to coherently analyse the impacts of the call auction suspension on NSE.

8.2 Summary of Main Findings and Conclusions

8.2.1 The Impacts of Non-Synchronous Trading On Predictability

The first empirical investigation employed various methodologies to model the predictability that non-synchronous trading effects may induce in the values of stock indices. Both daily data and higher frequency data were used in the investigation, since the latter is a prerequisite for capturing the typical intra-day variations in trading activity. Clear evidence of predictability between the Nifty and Midcap indices was obtained – in particular the Nifty index leads the Midcap index when considering a high frequency data set.

The investigation proposed a test involving the analysis of trading break returns to infer whether predictability is mainly attributable to non-synchronous trading or an actual delayed adjustment on part of traders. When analysing the trading break returns it was noted that the lead-lag effects persist, and in such cases the predictability cannot be attributed to traders' delayed expectation adjustments since during an overnight period market participants have sufficient time to adjust their expected values of stocks. Thus the investigation indicated that lead-lag effects are mainly caused by non-synchronous trading, and that the predictability is not likely to result in abnormal profit opportunities.

In line with previous studies, it was noted that non-synchronous trading is not the exclusive cause of the observed predictability. In particular, the feedback effect from the Midcap to the Nifty index may not be attributed to non-synchronous trading given that the former index is composed of less liquid stocks as compared to the latter. A smaller capitalisation index may lead a larger capitalisation one, when markets are responding to news which mainly impact on smaller companies. Other possible sources of predictability on securities markets include market participants who tend to allocate higher priorities to the monitoring of larger stocks, large orders being split into smaller ones, securities hitting price limits, and traders "picking off" mispriced limit orders submitted earlier on.

8.2.2 The Seasonality of Stock Price Volatility and Its Connection with Excessive Price Movements

The main aim of the second empirical chapter was to model volatility on NSE and to inquire whether it is justified or excessive. A battery of tests was applied to data sampled at different frequencies, and various instances of unjustified volatility emanating from the market setup or traders' behaviour were pinpointed.

Rather than adopting the standard methodology of comparing stock price changes to information about expected dividends, the research question was split up into two subsidiary ones. The first issue was whether the volatility is related to information flow, and this was tackled by applying existing theory on Monday effects and monthly seasonality to infer expected news patterns on NSE. It was then inquired whether volatility rises during those periods when new information becomes available. Increased volatility during the latter periods is likely to be the response to new information, and therefore it is more likely to be justified. The second related question concerns the relationship between volatility and returns. If volatility is considered as a measure of risk, finance theory would suggest that this should be positively related to returns. This question was investigated through GARCH-M models.

The analysis identified typical volatility patterns in the index data, in line with prior empirical papers. These include peaks in volatility during the opening and the closing of the trading day, as well as the presence of a Monday effect in index data. Tests revealed that the Monday effect in index data is more attributable to market microstructure factors such as non-synchronous trading, since the Monday effect is not significant in the underlying stocks. NSE volatility tends to increase during the months of March and April, and this may be explained through an end-of-financial-year effect, coinciding with the Indian end-of-fiscal-year. The increased NSE volatility during the month of March seems unjustified, since it is not accompanied by higher return magnitudes of similar statistical significance. The higher volatility during April is accompanied by higher returns of similar significance, and thus the pronounced April volatility seems related to new information, since the intra-day fluctuations materialise in returns at the end of the trading day. NSE volatility abates during August and this may be attributed to a holiday effect. Finally, EGARCH-M models show that longer-term volatility seems unrelated to the returns on NSE and this indicates that volatility may be excessive. Thus the analysis highlighted different features which may potentially constitute unjustified volatility.

The findings of this investigation were also rich in terms of providing important evidence regarding issues which were not directly related to the main research question. The finding of Madureira and Leal (2001) was confirmed, in that the Monday effect may appear in a stock index, but not in the underlying stocks. This shows the importance that researchers confirm Monday effects through individual stock data rather than relying on index data. The finding is also relevant from the point of view of market designers, since the Monday effect in index data might be due to index construction features or non-synchronous trading. The chapter also provided important evidence as regards the January effect often observed on other markets. The "January" effect on NSE was observed during the months of March and April, and this implies that it is likely that this effect is related to the end-of-financial-year of listed companies and/or the end of the fiscal year. The January effect is nonexistent on NSE during the month of January.

8.2.3 The Impact of the Suspension of Opening and Closing Call Auctions

The third empirical analysis considered the impact of the suspension of opening and closing call auctions by NSE in June 1999 – this may be considered as the focal point of the dissertation. It was firstly established that the software problems which seem the main cause behind the suspension, were not affecting the pricing process on the exchange and that probably the software glitches mainly occurred during the closing auction held on the day prior suspension.

The analysis compared the volatility, efficiency and liquidity of traded securities before and after suspension. In addition, the value of the auctions to shareholders was estimated using an event study to calculate the cumulative abnormal returns (CARs) for the sampled securities. Volatility, efficiency and liquidity broadly improved, although one measure of volatility deteriorated. It was noted that the abnormal returns during the event period were significant in terms of their magnitude, and their pattern was robust across different sub-samples of the stocks. Yet, we cannot speak of a clear-cut market reaction in terms of CARs since the latter were not uniformly positive or negative.

It was found that lower liquidity stocks traded less in the auctions as compared to other securities and they experienced the most gains following suspension. This is consistent with the observation of Schwartz (2000) regarding the pre-requisite of a "critical mass" of activity for auctions to be effective. Thus, the evidence suggests that opening and closing call auctions may not necessarily improve share trading in a less liquid emerging market.

Still, the findings do not allow us to dismiss the theoretical conclusions of authors such as Madhavan (1992) and Economides and Schwartz (1995) predicting more efficient information aggregation in an auction setup, since the adverse impacts of the auctions discovered in the study may have been the result of a badly structured auction or a setup which was inadequate for the underlying NSE characteristics.

8.2.4 A More Detailed Investigation of the Changes in Inter-Day and Intra-Day Volatility Following Call Auction Suspension

The fourth empirical investigation studied the volatility impacts of the call auction suspension in further detail, in view of the contrasting evidence obtained in the former chapter. The analysis employed more rigorous measures of volatility, and applied various tests, ranging from GARCH models to the scrutiny of price movements and return distributions during the day. Tests were conducted on monthly and daily data as well as observations sampled at higher frequencies. The original data set sampled at daily frequency was adjusted to take account of monthly seasonality of volatility as discovered in the second empirical investigation.

Tests on intra-day data pointed at a significant drop in the response of the conditional variance to lagged shocks as well as a highly significant drop in the unconditional variance following the call auction suspension. In addition the post-suspension period is characterised by lower volatility in the middle-of-the-day and the closing return distributions. The opening volatility was higher in the post-suspension period, yet tests on the reinforcements and reversals of price movements indicate that this higher volatility might have been justified. The reinforcement-reversal tests cast doubts as to whether any expected benefits of call auctions were materialising on NSE, since the call auction period is characterised by a relatively high amount of reversals of the opening returns.

Tests on the seasonally-adjusted daily data revealed that the log returns were higher in absolute value during the call auction period; yet one cannot be sure whether this is a remnant of the seasonal volatility pattern on NSE. Estimating an AGARCH process indicates higher conditional volatility in the call auction period through a positive dummy variable, although the latter is not significant at the 90% confidence level. Estimating separate AGARCH models for the "Before Period" and the "After Period" yields inferences in the opposite direction, in that the conditional volatility seems higher following auction suspension, and the impact of shocks (news) is more in line with an efficient market in the "Before Period".

Overall, the empirical evidence obtained was somewhat mixed, but no clear evidence emerged that call auctions on NSE were resulting in significant benefits. This is broadly in line with the conclusions of the previous investigation. Volatility seems higher during the auction period, although one cannot rule out that this is due to the news release patterns on NSE. One might also argue that the opening call auction was less effective than the closing one.

8.3 Contributions to the Existing Literature

Each of the empirical investigations endeavours to add knowledge to the particular sub-section of the market microstructure discipline covered in the research.

The empirical investigation on non-synchronous trading effects proposes a new methodology of inferring whether predictability is mainly the result of non-synchronous trading or whether it constitutes an actual delayed adjustment of traders' expectations. In this way, the analysis provided a new perspective on existing ideas. The findings of the chapter are directly relevant to the area of market efficiency, since factors such as non-synchronous trading and market participants "picking off" mispriced orders, may give the impression that traders are not adjusting their expectations immediately. This confirms the arguments that the main criterion for an inefficient market is the existence of profitable trading opportunities and not predictability. The investigation on non-synchronous trading effects differs from existing research in a number of ways. It was confirmed that non-synchronous trading effects may be detected through lead-lag effects in stock prices and it was formally shown that non-synchronicity tends to become more pronounced in high-frequency data given that the level of trading activity typically varies throughout the trading day. Prior studies tended to focus on the serial correlation structure or else lead-lag effects were tested for at lower sampling frequencies. This explains why previous studies conducted through lower frequency data such as Chiao, Hung and Lee (2004) did not detect any significant causality. Given that most of the prior literature was based on daily data, the typical surges in trading activity at the end of the day probably diminished non-synchronous trading effects, and this might have implied an under-estimation of non-synchronicity.

The empirical chapter on NSE volatility applied existing techniques to analyse the issue of excessive volatility in a novel way. Previous studies inferred whether volatility is excessive or otherwise by comparing stock price changes to information about expected dividends. Yet this approach cannot be readily applied to index data since stock indices do not directly yield dividends. In addition dividend data are inherently low frequency, implying that they are of limited use in the context of a high-frequency analysis. Thus, one main innovation of this investigation lies in the interpretation of different models and their possible connection with the detection of excessive volatility. These issues have not been sufficiently emphasised in prior literature. In addition, the analysis of NSE volatility fills a gap in the empirical literature related to the cause of the January effect – which when considering the Indian economy characteristics seems to be mainly related to the end-of-financial-year of quoted companies, coinciding with the end of the fiscal year.

The investigations of the effectiveness of the call auction setup on NSE, adopted a novel approach in considering the impact of the suspension of opening and closing call auctions. These are probably the first studies of the impacts of such a suspension, and feature the inherent strength that other market protocols and arrangements remained unchanged. This feature enhances the robustness of the conclusions, in that any changes following the suspension are more likely to have been the result of the change concerning the call auction, whereas in previous studies, changes were typically accompanied by other reforms which make it difficult to infer the actual source of the outcomes. The findings have some important general implications. They support the argument that call auctions are not necessarily a superior method for opening and closing an otherwise continuous market. One cannot support the notion that the main disadvantage of call auctions is that they prohibit stocks from trading continuously given that indications of further disadvantages in terms of volatility, efficiency and liquidity were obtained. The benefits or costs of call auctions appear to depend on the composition of the shares being traded. In addition, the evidence points that it cannot be taken for granted that an opening or closing call auction will improve share trading in a less liquid emerging market. On the NSE, it appears to have been precisely the less liquid securities which gained least from the call auction system.

8.4 Practical Implications of the Findings

The relevance of the above findings is not merely confined to the academic field, but also extends to market practitioners – with a particular relevance to market designers. One aspect which is common to the separate empirical studies tackled in the dissertation is market efficiency. Non-synchronous trading effects may be mistakenly interpreted as inefficiencies. Excessive volatility occurs due to market inefficiencies, and call auctions and other features of the trading setup are partly intended to increase pricing efficiency. In aiming to enhance pricing efficiency, market designers should endeavour to make information promptly available to the general markets. This should help in curtailing unjustified price movements and it should increase the efficacy of call auctions given that prices are formed using an updated information set.

The studies also suggest other practical policies which should improve the trading process. The first empirical investigation provided evidence of predictability on the markets and it was noted that one potential predictability source constituted smart traders "picking off" stale orders which were left unmonitored. In tackling this issue, exchanges should consider increasing the variety of permitted order types. In particular, systems might be tailored to accommodate immediate-or-cancel orders which are annulled if they remain unsatisfied for a period of time. Exchanges might also consider allowing adjustable limit orders, which are automatically updated depending on market movements.

The empirical investigation on NSE volatility pinpointed various instances of unjustified market movements. Monday effects in the index were attributed to market microstructure factors such as inappropriate index construction or non-synchronous trading. In case of the latter possibility, one may assume that the non-trading periods do not occur due to insufficient trading requirements given that the Nifty index used in the study comprises the most liquid stocks on the exchange. Thus, one course of action which may be considered is to inquire whether and why traders might be holding back orders on Mondays – possibly due to a higher degree of information asymmetry. When considering the unjustified price movements during the month of March, one important issue to be tackled is whether these fluctuations are indeed "harmful" to market stability. Whilst the deviation of prices from fundamentals tends to be undesirable, one should keep in mind that such deviations may not always be of significant concern and indeed the resulting speculation should help in generating liquidity and market activity.

The third investigation related to the efficacy of call auctions. This is of high relevance to finance practice, especially when considering that most order-driven markets initiate their trading sessions with a call auction. At times call auctions are also used to terminate the trading day, and to re-initiate trading following a mid-day break or a trading halt. The finding that the expected benefits of call auctions may not always materialise, might imply that market designers should reconsider the transparency of the process. For instance, in the case of NSE only the best five prices on each side of the market were disseminated. This means that if the market is sufficiently overvalued or undervalued the orders submitted by traders having "correct expectations" might remain undisplayed. Similarly, the inside spread which is disseminated to the market might be subject to market manipulation; say a trader who would like to sell a large number of securities might post an order to buy a much lower number of those securities at a relatively high price in an attempt to raise the market price. A related issue is whether the pre-auction prices are displayed to the market at large, since this might make it easier for participants to infer the fundamental value of the asset. Despite this, a possible trade-off between transparency and efficiency becomes apparent when one considers that transparency may facilitate trader collusion, that it may increase the potential for participants to misguide the market by submitting misleading orders and that it may exacerbate the "free option" problem relating to limit orders.

The investigation of the impacts of the call auction suspension on volatility yielded (contrasting) evidence which certainly does not constitute a case for the universal suspension of call auctions. Yet, the analysis is useful from the point of view of market designers who should avoid thinking of call auctions as a guarantee for lower market volatility. Thought has to be laid on the actual design of the auctions, the possibility that these might not attract sufficient trading activity, and whether they make sense in the particular circumstances.

8.5 Limitations of the Research

The limitations of the former investigations should be kept in mind in interpreting the results. One limitation which is common to most empirical research is that the behaviour of market participants is modelled as a time series whilst abstracting from modelling individual decision making behaviour, which depends on personal and possibly subjective factors such as risk-return tradeoffs, inventory holdings and the urgency to trade.

Other limitations emanate from the necessary assumptions made during the investigations. Throughout the dissertation, it was assumed that the index compositions do not change materially over the sample period. When using high frequency data, the sample of trading days was limited due to software restrictions and constraints on time available for the sampling process. The selection of a limited number of trading days leaves the possibility that the conclusions may have been peculiar to the particular period. Conversely, the daily time series typically spanned over longer periods – in some cases a five year-time series was used. The limitations inherent in working with such a long time period include the possibility of changes in market microstructure, most of which are unaccounted for. Some of these microstructure changes (for instance changes in price limits) may well affect the underlying volatility process.

Reference has to be made to the inherent shortcomings of the methodologies applied in the investigations. There are limitations relating to OLS regression estimation, which assumes the absence of heteroskedasticity of returns. Given that the latter goes against the empirically observed "stylised facts" of stock market data, this limitation was addressed through modelling heteroskedasticity, thoroughly analysing diagnostic statistics of the market models, and applying alternative techniques such as the Kruskal-Wallis test where appropriate.

A further methodological limitation is that GARCH methodology assumes that the error term follows a Markov process, despite contrary evidence that the error terms may depend on past values (Hansen; 1994). In addition, the GARCH processes utilised in the research exclude exogenous factors such as volatility on overseas markets.

The limitations of event study methodology were described in detail in the respective chapter. Whilst the significance and the CARs pattern were estimated and cross-checked through non-parametric methodologies, further limitations still remain. These include the possibility that the results obtained may be particular to the sampled stocks, and the inherent assumption that the market model coefficients remain unchanged over the estimation period and the event window.

Reference has to be made to the Reversal-Reinforcement tests which may be biased in favour of reinforcements (Madhavan, Richardson and Roomans; 1997). In addition, the underlying news pattern may occasionally mean that in some Reversal instances, the initial volatility may have been justified, and similarly Reinforcements do not necessarily justify the opening return.

Methodological limitations were discussed in more detail in the respective chapters.

One further limitation derives from the specific focus of the research in the sense that the topics should also be considered within a more general framework. For instance, the analysis of non-synchronous trading could also be assessed from a practitioner point of view, such as the possible price risk which may be induced due to the gap in between order submission and execution. The volatility investigation might have different implications when considered from the viewpoint of traders who regard volatility patterns as a profit opportunity. Similarly, the analyses of the call auction suspension abstracted from the possibilities that the auctions may have been of special relevance to specific trader categories such as institutional traders, or that they might have been more useful during higher volatility days.

8.6 Agenda for Further Research

The former empirical investigations point at possible directions which may be taken in future research projects.

The investigation on non-synchronous trading effects shows that the analysis of high-frequency data might offer potential for an even more detailed analysis of non-synchronicity. This rests on the notion that the increased trading activity at the opening and closing of the trading day reduces non-synchronous trading effects as compared to those prevailing during the rest of the day. In this way, most of the existing studies using daily closing prices might underestimate the degree of non-synchronicity. The analysis of individual stock high frequency data, offers potential for inferring how the degree of non-synchronicity varies across stocks with differing liquidity. In addition, further research is needed to shed light on the degree of predictability which may be exclusively attributed to non-synchronous trading as opposed to other sources of delayed price adjustment.

The second major issue covered in the dissertation related to the nature of volatility in terms of whether it may be deemed justified or excessive. Given the importance of this issue for market microstructure, the discipline would benefit from additional methodologies which may be applied in answering such questions, in the absence of data about dividend expectations. The absence of a significant relationship between NSE volatility and returns might imply that investors are not being rewarded in line with the price risk which they bear. This leads to the question of whether "smart investors" should be holding stocks for a long term period, or whether a better risk-return combination may be achieved by taking advantage of volatility patterns, as done for instance by day traders. The empirical results also confirm that further research is required as to why index data tend to feature a Monday effect which might be absent in the underlying stocks. This finding entails a critical evaluation of the traditional notion that Monday effects are caused by the accumulation of news during the weekend as well as the features in index construction which may lead to a spurious Monday effect in index data.

The investigations on the impacts of the call auction suspension were taken from the point of view of the general market. Whilst this may be considered as a sensible approach, further research may be undertaken to assess the desirability of call auctions to specific trader categories such as large institutional traders. Additional research is also required on the linkages between call auctions and other features of the trading setup since the efficacy of auctions on particular trading venues may also depend on other intricate elements involved in the trading protocol. The interaction between auctions and transparency may be one potential avenue for future research. The information dissemination features of call auctions should be enhanced within a transparent setup, yet transparency may also facilitate trader collusion or the misguiding of participants through the submission of mispriced orders (or imprecise information as per the experimental study of Brandouy, Barneto and Leger; 2003).

Overall, the investigations undertaken in this dissertation do not only offer contribution to finance practitioners and the academic field, but they also point at future directions which may be explored in further microstructure studies.

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